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Master's Degree in Mechatronic Engineering

Master's Degree Thesis

Design and Simulation of an Innovative System of Battery Swapping for Electric Vehicles

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"If you try anything [...] to make the world a better place,

you have already achieved something wonderful,

before you even begin."

Sarah Dessen, Keeping the Moon

Abstract

The automotive industry is currently facing a very dynamic decade in which new technologies, innovations and the progressive automation in the field of mobility are revolutionizing the way we drive cars. Concerning electric vehicles, their gradual spread and deployment in the transport sector, suggests that electrified powertrains will play an important role in near future global mobility and urban transport: the transition from conventional internal combustion engines (ICE) to electric one is finally at hand.
For this reason, many companies are engaged in the production or design of electric cars, but nowadays, the expensive costs of the electric car batteries and the high number of cells to be used to have autonomy comparable to those of internal combustion vehicles as well as the long battery charging times, hinder motorists from buying these types of cars. It is precisely from these last considerations that the idea of recharging the batteries of electric cars in a quick and practical way, exchanging them at a service station was born.
The thesis will discuss the efficiency of the battery swap system through the design and implementation of a simulation model of an innovative batteries management station for electric cars (EVs[1]) capable of replacing an exhausted battery with a fully charged one, eliminating waiting times for customers.
The sizing and operation of this station, called Battery Swap Station[2], will be investigated in this work through a configurable simulation model able to generate different scenarios taking as a case study the city of Turin.
The simulation model has been implemented in FlexSim, a 3D simulation modeling and analysis software. A series of experiments are then designed and simulated in order to show which factors could affect the performance of the station. Afterwards, several useful performance measures will be tracked and analyzed. Finally, through a multiple-criteria decision analysis (MCDA) approach, the most suitable solution is provided to the case study.

[1] From now on throughout the thesis, all vehicles for which an electric motor is the basis of the propulsion, thus including battery electric vehicles (BEV), are referred simply as EVs (Electric Vehicles).

[2] From now on, the term "battery swap station" is referred to as BSS

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1 Introduction

The thesis focuses on the smart management of the batteries of electric cars arriving at the Battery Swap Station (BSS). A simulation-based approach has been used to better evaluate the performance measures of the system involved and to have suitable and more realistic criteria to encourage the automotive industry and private companies to invest in this field. The simulation model includes from when the discharged battery arrives at the station to when the charged battery comes out.

The thesis is composed of six chapters and it is structured as follows:

- *Chapter 1:* introduces the concept and gives a brief description of the battery swap method, its major providers, its benefits as well as its difficulties, and defines the rationale behind choosing this innovative batteries management and utilization system

- *Chapter 2:* points out the current situation regarding battery swapping technologies, implementations and techniques available today, taking into account the relevant studies and research in scientific literature

- *Chapter 3:* contains the description of the scenario considered in this work to design and simulate an automated station for EVs battery swap. Moreover some assumptions have been formulated for model building

- *Chapter 4:* provides a comprehensive explanation of the model built in FlexSim simulation software, as well as the proposed plan of experiments and the performance measures observed

- *Chapter 5:* highlights the results obtained by the simulations with regard to the benchmarks, feasibility and performance of the proposed model, finding also the best solution between different alternatives. At the end a further improvement to the model is provided

- *Chapter 6:* draws the conclusions, makes it clear what are the thesis findings and addresses proposals for future related developments and work ideas

1.1 The Electric Vehicle Market

The current transport system has a significant negative impact on the environment and on human health because it depends mainly on high oil consumption (with the resulting emission of greenhouse gases and particulates into the atmosphere). Given the positive contribution of the development of electric mobility to environmental sustainability and to changes in driving habits, especially on short journeys, data on the modern situation of EVs are briefly reviewed.

EVs or BEVs are all those vehicles equipped with an electric motor powered by electricity, which is supplied by a pack of rechargeable lithium batteries usually located at the bottom of the vehicle (Figure 1.1).

A recent research carried out by Boston Consulting Group[3] found that the future of mobility will depend on three main factors: autonomous driving, electric and shared vehicles and furthermore by 2030, electric vehicles will account for about a quarter of all cars and trucks on the road and 50-60% of sales of new cars [1]. In addition, since the rapid technological progress in energy density is leading to a reduction in battery costs, BCG estimates that by 2028, the total five-year cost of ownership for an electric vehicle battery in the United States will be lower than for an internal combustion engine vehicle [2].

Right now, we are really going in that direction: many nations and governments are actively working to promote the reduction of air pollution, fossil fuel use and CO_2 and greenhouse gas emissions. As a result, EVs have gained significant market share over the last decade worldwide, especially in China with more than 1 million electric cars sold in 2018, followed by Europe and the United States with approximately 400 thousand and 350 thousand electric cars sold respectively from the previous year as confirmed by data taken from the Global EV Outlook 2019 (Figure 1.2).

[3] BCG is a U.S. multinational strategic consulting firm

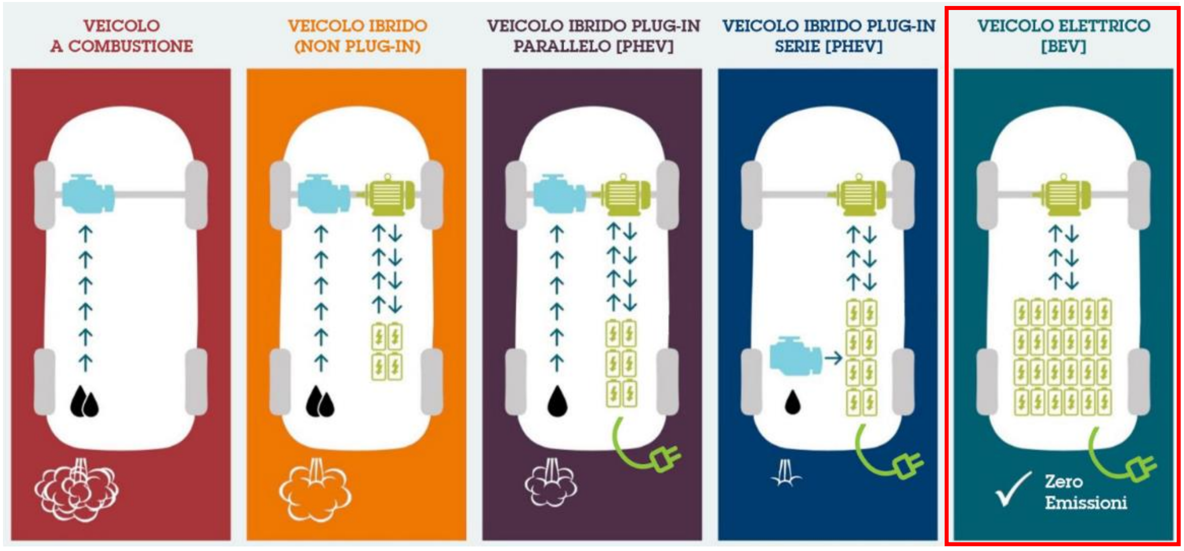


Figure 1.1 Main existing vehicles by type of supply [3]

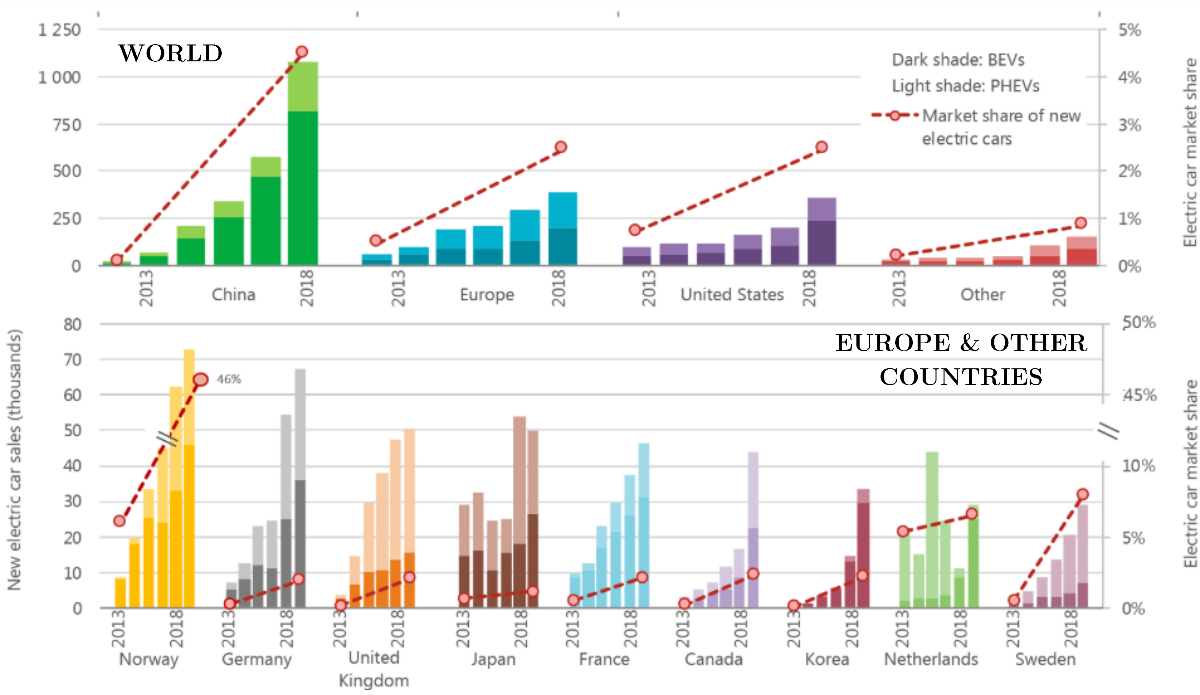


Figure 1.2 Global electric car sales and market share in the world and part of Europe, 2013-18[4] [4]

The major factors driving the growth of this market and so the roll-out of EVs include adoption of policies to promote the purchase of electric vehicles like financial incentives, battery rental options, subsidies, economic benefits such as tax reductions, reduced parking and toll rates, free movement on highway networks, removing access restrictions

[4] Source: IEA analysis based on country submissions, complemented by ACEA (2019); EAFO (2019); EV Volumes (2019); Marklines (2019); OICA (2019). Other countries includes Australia, Brazil, Chile, India, Japan, Korea, Malaysia, Mexico, New Zealand, South Africa and Thailand

to limited traffic zones in certain urban areas, etc. Policies have a major influence on electric mobility as EVs purchase prices are higher than for ICE vehicles.
In Italy, sales figures for electric cars are rising steadily as the electric car market is characterized by a growing trend in recent years and, even though the number of EVs registered is low compared to other EU countries like Norway and Germany, the indicators suggest an increasingly widespread propensity to buy electric cars (see Figure 1.3). Registrations of full electric cars in 2018 have more than doubled compared to the previous year (+147.3% w.r.t. 2017), rising from just over 2000 to almost 5000 cars. Despite the fact that private vehicles are still the preferred means of transport for daily urban travel (more than 50%) [5], other forms of e-mobility such as electric public transport services (electric buses and electric taxis) or electric car/scooter/bike sharing services are taking hold and could become the most common driving modes of the next decade.

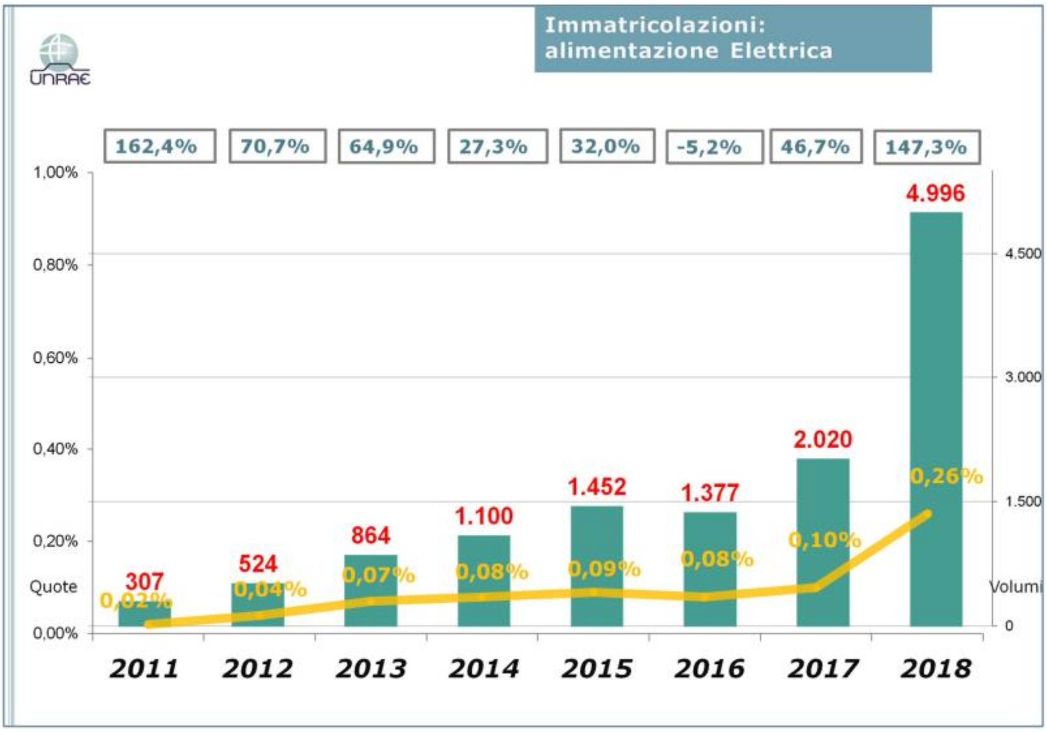


Figure 1.3 Electric vehicle registrations in Italy [6]

1.2 Charging EV's battery pack

Nowadays, three main battery charging ways for EVs, that require different types of infrastructures and technologies, are available (as can be seen from Figure 1.4):

1. *Wired charging*: this method consists in the direct physical connection between the electric vehicle and the charging infrastructure which includes a wall outlet, designed to dispatch AC or DC power, and a power extension cord (single-phase or three-phase). For this process, there is a further division depending on the powers used

2. *Inductive (wireless) charging*: instead of plugging the car into an electrical outlet, this technology will charge the vehicle's battery using an electromagnetic field generated when the vehicle is parked above a ground charger (no need for chargepoints)

3. *Battery swapping*: the driver has only to park the car in the designated area of the station and then the automated system reveals the presence of the car, aligns it in the right directions, disconnects the discharged battery from the vehicle, transports it to the warehouse to charge it, picks up a charged battery ready for use and installs it on the vehicle

Energy source	GASOLINE/DIESEL	HYDROGEN	BATTERY		
	Fueling gasoline or diesel at a petrol station	Fueling hydrogen at a hydrogen refueling station	"Wired" charging using a plug	Battery swapping	Induction charging
Description	Conventional gasoline or diesel refueling	Hydrogen refueling (similar to natural gas refueling)	Plugging in to a charging station using a cable and plug	Replacing a battery for a fully charged one at a special swapping station	Battery in the car is charged by wireless induction charging
Time needed¹	5 min	5 min	4-8 hrs (slow) 20-30 min (fast)	5 min	~2-8 hrs²
Suitable for which power-trains	▪ ICE ▪ HEV ▪ PHEV ▪ REEV (gasoline)	▪ FCEV ▪ REEV (hydrogen)	▪ PHEV ▪ BEV suitable for plug-in charging	▪ Special BEVs suitable for battery swapping	▪ Special BEVs suitable for induction charging
Example car	▪ All ICEs	▪ Hyundai ix35 (FCEV)	▪ Renault Zoe (BEV)	▪ Special model of Renault Fluence	▪ N/A (few pilot cars)
Current availability in Europe	Widely available: ~131,000 stations	Very limited: ~80 stations	Limited availability: >20,000 (slow) >1,000 (fast)	Very limited ~50 stations	Not available (few pilots in progress)

1 Time need for full refueling or recharge. For fast-charging of battery, time to reach 80% of battery capacity is commonly used
2 Since induction charging is still in pilot stage, common duration and power level are not yet established; power levels of 22 kW have been achieved

Figure 1.4 Electric powertrains: charging infrastructures archetypes [7]

Internationally, the reference standard for charging stations (wired or inductive) is defined by the International Electrotechnical Commission (IEC) and is the IEC 61851-1 standard. This regulation specifies the general characteristics of charging systems, including charging and connection modes and safety requirements.

In the current market, Lithium-based batteries, already extensively used in consumer electronics devices, are often employed in EVs both for their high energy density and for long cycle life.

The battery of an EV can be charged mainly in two ways: via alternating current (AC) using the power distribution grid or via direct current (DC). By default, the battery pack of an EV is always charged in DC (see Figure 1.5).

Especially in the first case (AC), which is the case of low power charging systems (up to 22 kW), there is a need for an AC/DC conversion block that converts the alternating current into direct current. This block is essentially a rectifier and is located inside the electric car as an on-board battery charger. In this way, the charging station acts as a simple dispenser and so the effective charging power depends on both the power of the system and the maximum power accepted by the on-board charger. The AC charging can be single-phase (230V) or three-phase (400V) and since the chargers integrated in EVs are not all the same, some accept higher powers (e.g. 22 kW - 32A 400V) and others accept lower powers (e.g. 3.7 kW - 16A 230V).

By taking as an example an on-board battery charger that allows a maximum power of 7.4 kW and connecting the car to a 3 kW domestic electric system, the charging will be at 3 kW because this is the maximum power available. On the other hand, if the same car is connected to a system that delivers 7.4 kW but its on-board battery charger is 3.7 kW, the charging would still take place at 3.7 kW, which is the maximum at which the on-board charger can work. Briefly, the on-board battery charger of the vehicle sets the power limit.

With the other alternative (DC), typical of fast charging systems whose power exceeding 22 kW, the direct current is sent directly to the car battery without going through the on-board charger (this happens because the rectifier is within the charging infrastructure acting as an external charger). This charging mode is more complex and more expensive than AC charging, but allows to exceed the limits of the charging power of the battery charger inside the vehicle, to accommodate much higher charging currents and thus to shorten the charging time. However, in order to avoid overstressing the battery and increasing its internal temperature, this type of charging is limited to 80% of the battery capacity (in practice charging times for high power chargers are often indicated at 80%).

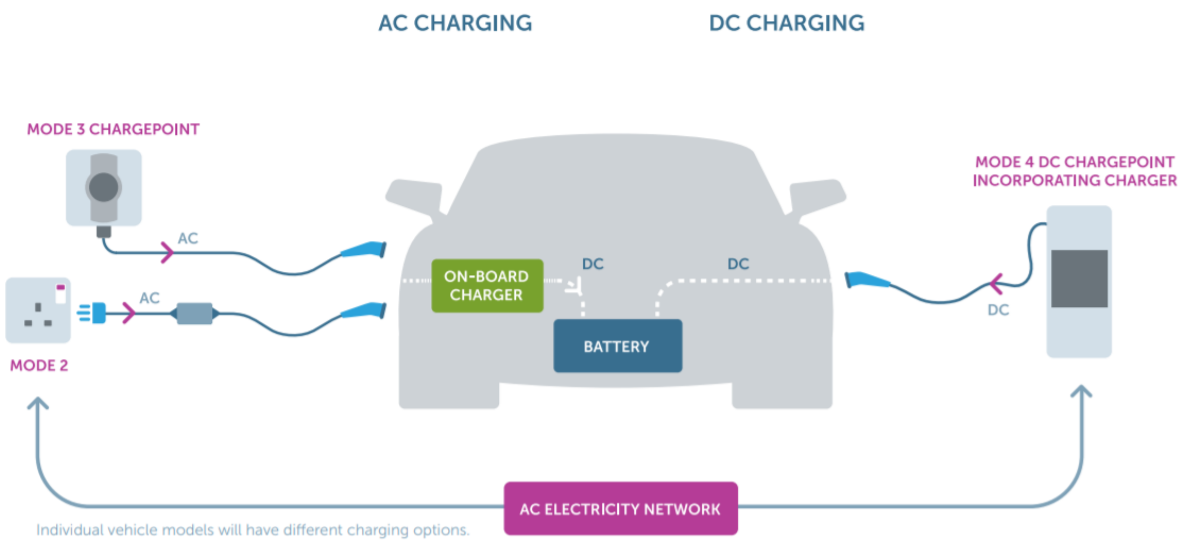


Figure 1.5 Infrastructure elements of EV charging [8][5]

For that reason, charging time is a very important parameter to consider because a battery pack cannot be charged at an arbitrarily high speed. Both the voltage and the current influence the rate of charge: for example when charging at 7.4 kW this is generally done at 230 V and 32 A (230 V * 32 A = 7360 W ≈ 7.4 kW).
The battery charging time of an electric car is dependent on 3 key factors including the charging speed, which, in turn, depends on the charging power available (measured in kW) in the charging station subject to the maximum power accepted by the vehicle on-board charger or by the infrastructure charger; the capacity (measured in kWh) of the EV's battery pack (that corresponds to the equivalent of the tank capacity of a car with a thermal engine) and the charge level (in percentage) of the battery relative to its capacity (i.e. the State of Charge, aka SoC[6]).
Hence, knowing these factors, to estimate the time needed for a complete charge of an EV's lithium-ion battery pack, it is sufficient to subtract the current capacity, determined by the SoC, from the usable battery capacity (thereby obtaining the amount of charge required) and divide it by the rate of charge, that is the charging power of the battery charger (inside or outside the vehicle) [8]:

[5] Mode 2: Home or business AC charging (home charger or wall-box); Mode 3: AC charging for public environments; Mode 4: Direct DC charging
[6] From now on the battery state/level of charge will be called SoC

$$\frac{\overbrace{UBC\ (kWh) - ABC(kWh)}^{\text{Amount of charge required (kWh)}}}{MPBC\ (kW)} = ECT\ (hrs)$$

Where:

- *UBC* is the Usable Battery Capacity
- *ABC* is the Actual Battery Capacity
- *MPBC* is the Maximum Power of the Battery Charger
- *ECT* is the Estimated Charging Time

The battery pack of an electric car is never used 100%. The usable capacity is less than the full capacity of the battery (it corresponds to about 90% of the total capacity) due to safety reasons such as maintain a correct battery temperature.
It is important to notice that even the battery chemistry affects the charging rate and a partial charge is also possible: in this case, the times are reduced proportionally.
Although EVs share these factors that affect time taken to charge the battery, the impact of each factor is different for each vehicle make and model. Indeed, since battery pack sizes vary considerably between EVs, charge times will vary accordingly.
Below are an example of charge times based on a 24 kWh battery pack (Table 1.1) and the charging times with the battery packs parameters of some of the best-selling electric car models in Italy (Table 1.2) in order to provide a reasonable comparison. Both for Table 1.1 and Table 1.2, charging time calculations are theoretical.

	MAXIMUM POWER OUTPUT FROM EVSE (KILOWATTS)	EXAMPLE CHARGING TIME (HRS:MINS)	INPUT VOLTAGE (VOLTS)	MAXIMUM CURRENT (AMPS)
AC	2.3kW	8hrs 20mins	230 1-phase AC	10
	3kW	6hrs 30mins	230 1-phase AC	13
	3.7kW	5hrs 15mins	230 1-phase AC	16
	7.4kW	2hrs 35mins	230 1-phase AC	32
	14.5kW	1hr 20mins	400 3-phase AC	21
	22kW	55mins	400 3-phase AC	32
	43kW	30mins	400 3-phase AC	63
DC	20kW	1hr	400 3-phase AC	40
	50kW	25mins	400 3-phase AC	100
	100kW	15mins	400 3-phase AC	200

Table 1.1 Example of charge times for a 24 kWh battery pack [8][7]

[7] EVSE = Electric Vehicle Supply Equipment (covers all the EV charging equipment)

Brand and Model	Number of Battery Pack Cells	Nominal capacity [Ah] & Voltage [V] of each cells	Battery Pack Weight [kg]	Battery Pack Capacity [kWh]	Energy Density [Wh/kg]	Maximum power of the on-board battery charger [kW]	Estimated Charging Times [hrs] for a full charge (0% → 100%)
Renault Zoe Z.E. R110 40	192 in 96s2p configuration	63.4 & 3.8	305	45.6 (available 41)	150.0	Single-phase: up to 7.4; Three-phase: up to 22	2.3 kW -> 24; 3.7 kW -> 14; 7.4 kW -> 7; 11 kW -> 4; 22 kW -> 2
Renault Fluence Z.E.	192 (96s2p configuration) in 48 modules	65.0 & 7.5	290	23.4 (available 22)	80.7	Single-phase: up to 3.7	2.3 kW -> 9.6; 3.7 kW -> 5.9
Nissan Leaf	192 in 96s2p configuration arranged into 24 modules	32.5 & 3.8	209	40.0	188.0	Single-phase: up to 7.4	2.3 kW -> 17.4; 3.7 kW -> 10.8; 7.4 kW -> 5.4
Tesla Model 3	4416 in 96s46p configuration	5.0 & 4.2	480	92.0 (available 75)	191.7	Single-phase: up to 7.4; Three-phase: up to 11	2.3 kW -> 32; 3.7 kW -> 20; 7.4 kW -> 10; 11 kW -> 6.8
Tesla Model S	7104 (6s74p configuration) in 16 modules	3.0 & 3.8	540	81.0 (available 75)	150.0	Single-phase: up to 3.7; Three-phase: up to 11	2.3 kW -> 30; 3.7 kW -> 19; 11 kW -> 6.3
Audi e-tron 55	432 in 36 modules	60.0 & 3.3	700	95.0 (available 83.6)	135.0	Single-phase: up to 7.4; Three-phase: up to 11	2.3 kW -> 41; 3.7 kW -> 25.6; 7.4 kW -> 12.8; 11 kW -> 8.6
BMW i3	96	120.0 & 3.7	278	42.6 (available 42.2)	153.2	Single-phase: up to 7.4; Three-phase: up to 11	2.3 kW -> 16.5; 3.7 kW -> 10.2; 7.4 kW -> 5.1; 11 kW -> 3.4

Table 1.2 Summary of battery packs parameters & charging times

The charging rate does not always behave constantly or at its maximum rate: in fact, depending on the electric car model used, it progressively decreases as it approaches 100% of the battery capacity. This particular event is more evident as the charging power increases. Consequently, at high rates the battery charge will reach very quickly a value of charge (SoC) beyond which the charge rate will progressively reduce. The chart in Figure 1.6 demonstrates the effect of different charging rates for four type of power chargers.

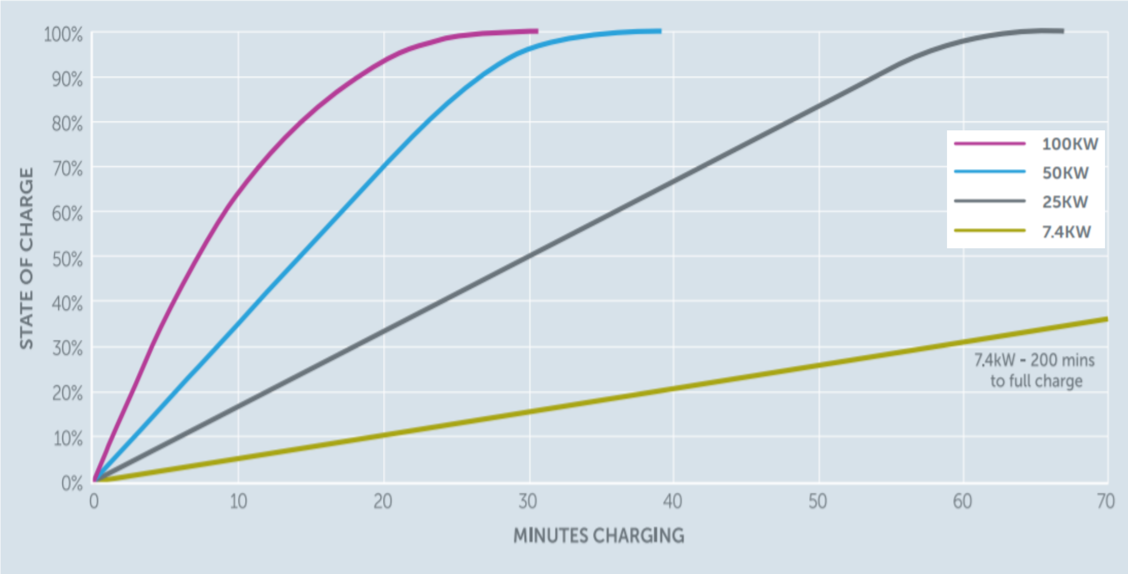


Figure 1.6 Impact on charge rate as battery fills [8]

The experimental results show a linear trend for charging curves with 7.4 kW and 25 kW up to 90% of the SoC. On the contrary, it is evident that at higher powers (50 kW or above) there is a non-linear pattern.
It is important to point out that the charge curve of each electric vehicle on the market is different and depends on the design choices accomplished by the vehicle manufacturer.

1.3 Motivation and critical issues

In practice the more the charging speed increases, the higher the current increases and consequently the more the heat produced by the internal resistance of the battery increases (following the well-known quadratic law of the Joule effect). This phenomenon taken to its extreme consequences causes an excessive increase in battery cells temperature with damage or destruction of the battery itself.
For illustrative purposes, the case of Tesla's Supercharger is taken into consideration. This system is a 480-volt DC fast-charging station, which provides up to 150 kW and takes about 30 minutes to charge 80% of the 85 kWh Tesla Model S.
The power level required by Tesla's Supercharger is so high that part of the transferred energy is lost and converted into heat (Joule effect heat dissipation). The power dissipated by the Joule effect on the charging station components increases with the square of the current intensity. This leads to a discrepancy between the amount of energy that reaches the battery (which is less) and that taken from the power grid.

Some sources have shown that the charging rate is related to the charging damage to the lithium-ion batteries. In particular, a study [9] reveals that the degradation of Li-ion battery cells at fast charging is faster and irreversible. Indeed, scientists, examining lithium-ion batteries by X-ray during rapid charging, have noticed the formation of holes in some areas of the electrodes that can no longer be used for energy storage, and a reduction in terms of lithium available to carry charges between the electrodes (lithium plating). The internal structure of the electrodes is then irreversibly modified and the degradation of the battery accelerated.

In summary, with the use of a high power (fast) charger, the damage to the battery would be considerably higher than with a low power (slow) charger that thus has small impact on battery life.

Thereby, current fast-charging technologies, such as Tesla Superchargers, are not the best option for charging batteries, because they stress and overheat the battery of EVs, resulting in energy loss. This in the long-term (i.e. after many charging cycles) leads to battery damage, significantly shortening the life and the battery's capability to maintain the charge over time.

Besides, energy losses inevitably occur in the battery charging system and they are mainly due to the devices used in the charging process. These elements include the rectifier that converts alternating current (AC) to direct current (DC), the length of the connection cable between the battery and the power source and the performance of the battery charger itself. This means that the more the power (kW) increases (and also the current), the more dissipation losses occur and as a result a slow charge is more efficient and disperses less energy than a fast charge.

On the contrary, the battery swap solution allows to regulate and smooth out the power demand peaks, limiting the negative effects of charging load on urban power grid, through proper charging load control strategy. Battery swap improve charging efficiency avoiding to accumulate excessive stress for the batteries while extending batteries' life times and leading to a significant saving of energy dissipated by the Joule effect due to high power charges.

Despite significant technology developments and enhancements in battery chemistry with regard to energy storage capacity and faster recharging are expected, battery swapping remains the fastest and safest way to restore an EV's range so far without damaging the battery pack.

Unfortunately, this method is not exempt from several problems related to EV manufacturers that work on this technology. In particular, to date, due to safety, feasibility and liability issues, the OEMs (Original Equipment Manufacturers) prefer to control their design strategies and so there is no compatibility between different car brands or car models and no establishment of a common standard on EV Lithium-Ion battery packs, dimension, type and configuration. Since each battery pack design is different, it would be very expensive to create a network of BSSs with different battery models and it is well known that the design of a BSS has very high cost implications.

For that reason, to take off this technology, there is a need to establish similar interchangeable battery packs for different manufacturers with common access to the battery compartment for all cars.

Another important issue to consider is related to the location and setup of the network of vehicle service stations, which must be well established and fit homogeneously into the urban context respecting the existing rules and regulations.

However, these are just some of the issues and technical challenges concerning current battery swap technology that researchers have to deal with in near future.

1.4 Background and Context

Yet still today, the major concerns hindering the wider take-up of electric vehicles are chiefly related to high investment costs (the battery pack can be excessively heavy and bulky for passenger comfort and it can be up to 50% of the cost of the entire vehicle) and technological issues such as the poor autonomy caused by low battery capacity, the time needed to recharge the battery pack at chargepoints, the lack of charging infrastructures (charger locations and availabilities) and battery life-span. All these factors lead, especially for long travels, to the resulting range anxiety issue, i.e. the fear that a vehicle may not have sufficient range to reach its destination and would therefore strand passengers.

Major research and development engineering centers worldwide are currently working to improve the range of EVs and to reduce battery-recharging times.

Given this reality, it is easy to understand how the battery swap solution constitutes a well-founded choice to overcome these barriers. This method consists in replacing the exhausted battery from underneath the car with a charged one at a fully automatic station, which is fitted with spare batteries that are already charged and ready to be replaced when needed (see Figure 1.7). The station, called Battery Swap Station (BSS), is equipped with a structure capable of performing the operation in an automated manner, typically a mechanical carriage and a robotic arm/system. The depleted swapped batteries are sent to a storage unit where they will be charged. In other words, this service is very similar to the current service that gasoline stations provide to internal combustion vehicles.

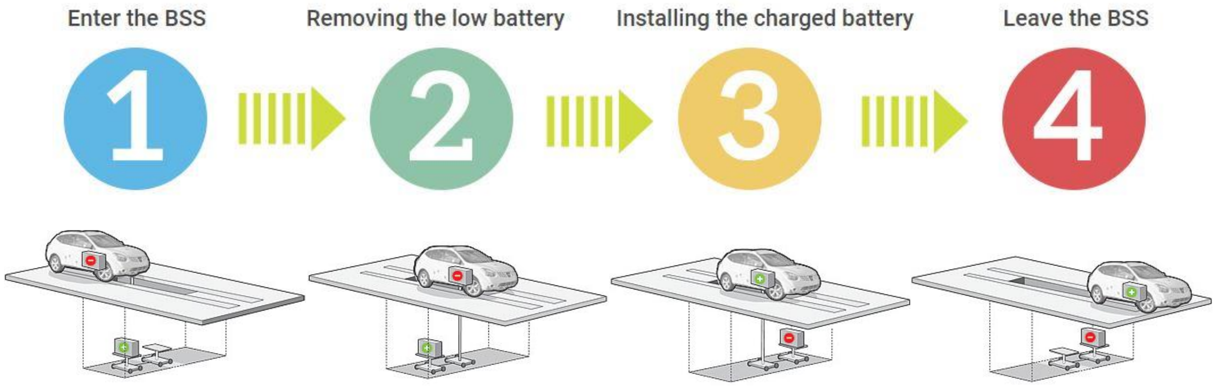


Figure 1.7 Battery swap process phases - Illustration by Pete Sucheski

In addition, there are many benefits offered by the battery swap system over conductive or inductive charging not only for EV owners, but also for station/battery owners. Table 1.3 shows the list of the main features, with strengths and weaknesses, of this technology.

Pros	Cons
Quick replacement of the depleted battery pack: Battery swapping time (under 3 minutes) less than refueling/recharging at filling stations	Need for a space to store the batteries to be exchanged and recharged
The procedure is automated, so the driver does not need to get out of the car or He is free to do anything else while the battery is swapped.	High costs of setting up the automated exchange platform from station provider
EV owner no longer has to worry about battery life thanks to increasing driving range (depending on stations availability) & Reduced range anxiety.	Requires an innovative business model and also the creation of an efficient widespread network of stations from infrastructure providers
Reduced purchase price for drivers because They do not own the EV's battery: the costs for battery maintenance and warranty are borne by the battery owner	Not all vehicles are suitable for battery swap because the batteries to be changed must be easily accessible and located in a single pack under the car.
This procedure does not overheat or damage/shorten battery life compared to fast charging.	High electrical energy demand generated by recharging the batteries to be met by the suppliers
Controlled scheduling of battery charging (e.g. charging batteries during night or off-peak hours) that increases the battery lifetime	Potential creation of a monopoly on the ownership of batteries by a third-party and technologies protected by patents

Table 1.3 Pros & Cons of Battery Swap Technology

A survey was conducted last year [10] on a sample of about 800 people coming from Europe which aims at deepening consumers' views on electric vehicles and obtaining information on people's perception of battery swapping. The results of this survey show that more than half of the respondents believe that EVs will completely replace gasoline-powered cars over a ten-year time horizon, but at the same time less than 15% of the

respondents, in everyday life, would consider using of battery swapping stations except for the lack of charging infrastructure or simply because it is more convenient.
As it is evident, EVs are generally well accepted by majority of people in industrialized countries, but uncertainties remain. Likely, the idea of leasing part of the car like the battery, and swapping it, potentially does not attract drivers. Maybe the battery swap technology is not yet mature enough and this could lead to safety problems (e.g. chemical, electrical, and fire risks). Moreover, there are still few charging stations and maintenance services for EVs and it is quite clear that users who would consider the purchase of an electric vehicle, require characteristics similar to those of modern internal combustion vehicles, especially in terms of performance, range, price and recharging/refueling times.

1.5 Business Models

The concept of battery swapping is not new, in fact, it dates back around a century ago, but it has been possible to put it into practice, using appropriate facilities, only in more recent times. Different business models and solutions have been developed. The first company to develop an ambitious business model based on the battery swap and the idea to separate the car ownership from battery ownership was *Better Place*[8]. The battery swap process was fully automated and the battery was exchanged within about 3 minutes through a robotic arm that removed the exhausted battery from underneath the car and replaced it with a full one. The first electric car enabled with battery swap technology and deployed by the company was the Renault Fluence Z.E. However, *Better Place* announced bankruptcy in May 2013 due to the huge investments needed to design and develop both the charging and the battery swap infrastructure (each Battery Swap Station cost about $ 500,000 [11]). Figure 1.8 illustrates the basic design of the Better Place's BSS while in Figure 1.9 it is possible to see the Better Place battery swap facility at Amsterdam's Schiphol airport.

[8] Founded in 2007 and based in Palo Alto (California), it was a venture-backed company mainly active in Israel.

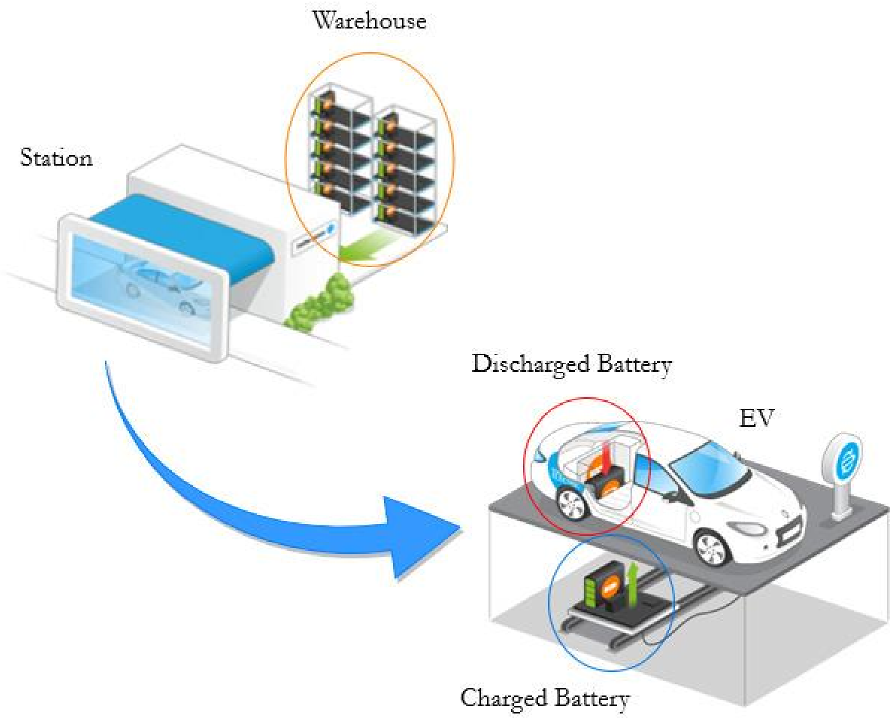


Figure 1.8 Conceptual design of a BSS (Better Place)

Figure 1.9 Better Place electric car BSS at Amsterdam's Schiphol airport[9]

Also the well-known Californian company *Tesla Motors,* in 2013, introduced the battery swapping technology for their EVs (for Model S, Model X and Tesla Roadster) to extend driving range replacing the battery pack in about 90 seconds. Tesla's business model, unlike that of Better Place, does not offer the option to lease the battery. Nevertheless,

[9] Credit: https://www.pluginindia.com/blogs/electric-car-battery-swap-stations

in the last few years it is exploiting the battery swap system as a service to support a network of fast-charging stations scattered throughout the United States called Supercharger able to charge up to 80% of a battery in 30 minutes.

In Italy, the noteworthy companies involved in the design of automatic battery exchange stations are *Picchio* and *Ecospazio*. The former is engaged in research and design of hybrid and electric road cars, while the latter belongs to the Green Mobility division of *Logiss Srl* and it is dedicated to the construction of charging systems and infrastructure that can be easily transported and installed for the use of EVs such as the EES (Energy Exchange Station).

In East Asia, particularly in China, countless companies are developing a new approach to urban transport. Among these, *Kandi Technologies Group* and *NIO* stand out. The first company, *Kandi Technologies Group*, which bases its business model on the electric car rental and car sharing, has devised a quick battery replacement system called "Quick Battery Exchange" (QBEX), which involves the lateral extraction of batteries from the vehicle by means of an automated robotic arm that deposits the exhausted batteries on a charging shelf from which it will then pick up the charged batteries and put them back into the vehicle. No special structures or transport systems such as forklifts, conveyor belts and so on are required.
The Chinese automotive brand for electric vehicles *NIO* was founded in 2014 and it has put into practice a battery swap service called "*Power Swap*" in 12 cities (across China and the world) including Shanghai, Beijing, San Jose, Munich, London and 7 other locations. The company's network of battery swap stations, called *NIO Power* division, has 18 battery swap stations (like the one in Figure 1.10) along the G4 Expressway in China, which extends for about 2,273 km.

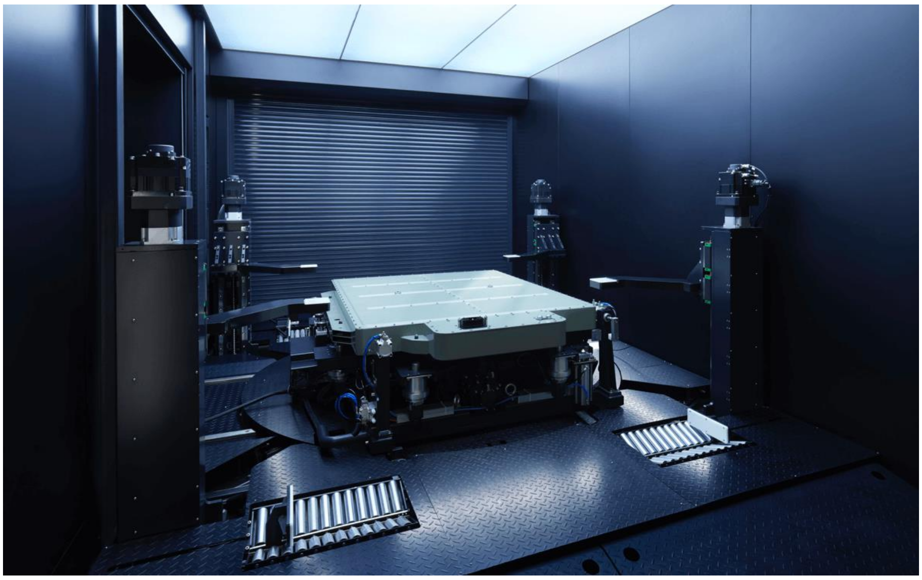


Figure 1.10 External and Internal view of NIO Power Station[10]

[10] Credit: https://www.nio.com/nio-power

2 State of Art

Following different criteria and points of view, many studies have been carried out and many others are currently underway dedicated to the study and analysis of this alternative strategy to the traditional recharge of the battery in electric cars, in order to understand whether it is a feasible solution.
This section is intended to investigate the battery swap system's players involved (the EV owner and the station owner), how the battery swap procedure takes place in EVs and all the related aspects, following the most recent developments published in scientific literature.

2.1 Related Work

The system architecture of the BSS is substantially equipped with the following main units:

1. distribution transformer to convert the volt to the charger's nominal input voltage from grid power system
2. chargers to convert AC power to DC power to charge the battery packs
3. rechargeable battery packs to provide energy to the EVs
4. battery pack replacement equipment/battery swapping system to replace an exhausted battery pack with an fully charged one
5. battery pack storage warehouses, battery pack conveyor shuttles and battery storage racks and rails
6. Other station units and control systems

Both the structural design of the BSS model and the architecture of battery placement in the vehicle are point out in the U.S. patent [12] issued to Tesla Motors, Inc. The patent describes in detail the main components of a BSS and all the steps for the exchange of an Electric Energy Storage System (EESS), i.e. a battery pack, in an electric vehicle. The patent application refers to swapping Tesla Model X or Model S battery packs. The method includes the following sequence of operations that has been reported as presented in the patent [12]:

1. *positioning an electric vehicle in x and y directions on an EESS exchange station*
2. *after positioning, raising the electric vehicle to a predetermined height using a first lift*
3. *after raising the electric vehicle, raising an EESS lift toward the electric vehicle until the EESS lift is correctly positioned relative to a first EESS*
4. *after raising the EESS lift, removing fasteners that secure a first EESS to the electric vehicle*
5. *placing an EESS conveyor underneath the EESS lift*
6. *after placing the EESS conveyor, lowering the first EESS onto the EESS conveyor using the EESS lift*
7. *after lowering the first EESS, removing the first EESS and instead placing a second EESS underneath the electric vehicle*
8. *after placing the second EESS underneath the electric vehicle, raising the second EESS toward the electric vehicle using the EESS lift until the second EESS is correctly positioned relative to the electric vehicle*
9. *after raising the second EESS, fastening the second EESS onto the electric vehicle*
10. *after fastening the second EESS, lowering the electric vehicle using the vehicle lift*

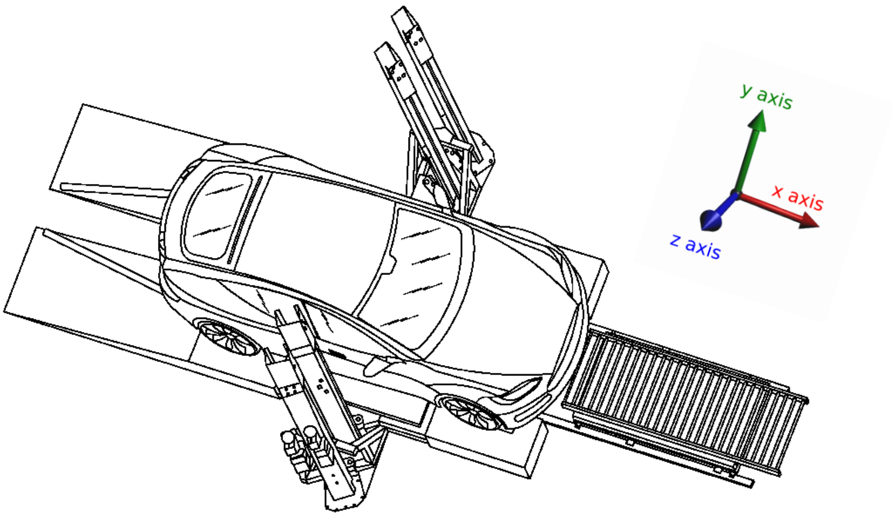


Figure 2.1 The sketch shows the vehicle that creeps forward until it is correctly positioned in the x direction [12]

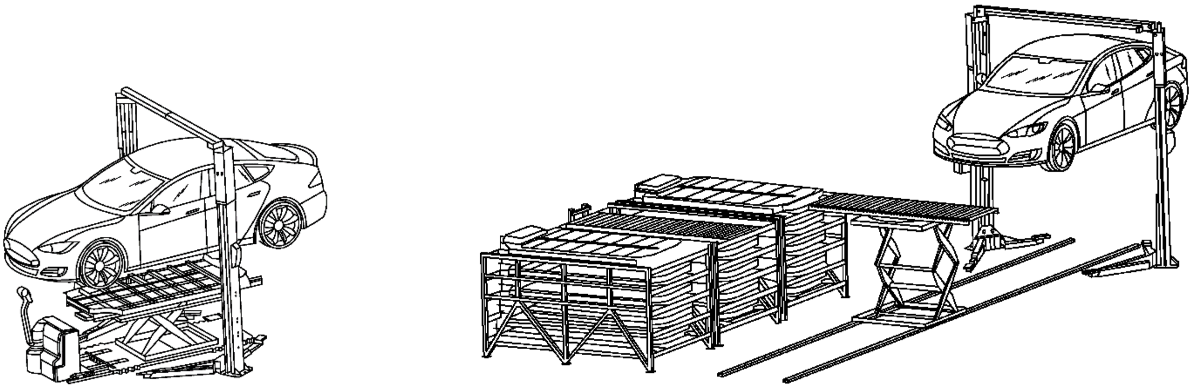
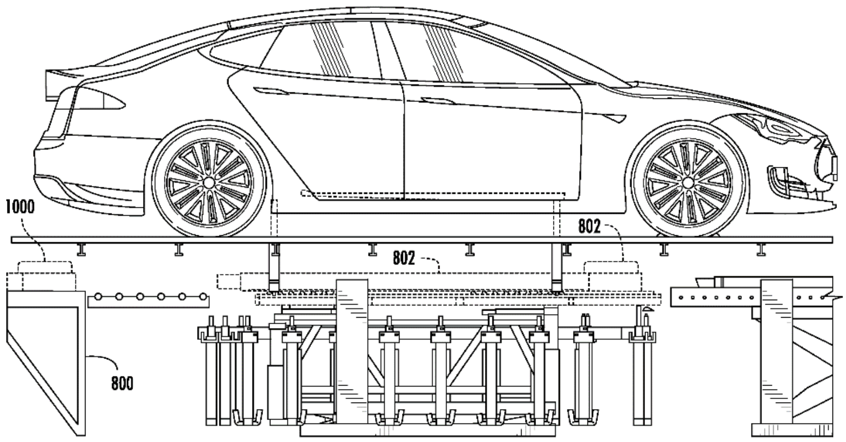


Figure 2.2 The sketch shows a forklift used to raise and lower the battery pack and a moving device for battery packs positioned on rails in order to move between battery storage and the serviced vehicle [12]

While in another patent [13], always filed by Tesla Motors, Inc., a platform with a battery pack lift system and other systems to hold and move the battery packs are presented. The lifting system includes a frame on which screwdrivers are mounted, a lift configured to raise and lower the frame, and two air bearing configured to allow relative movement between the frame and the lift and between the battery pack and the frame.



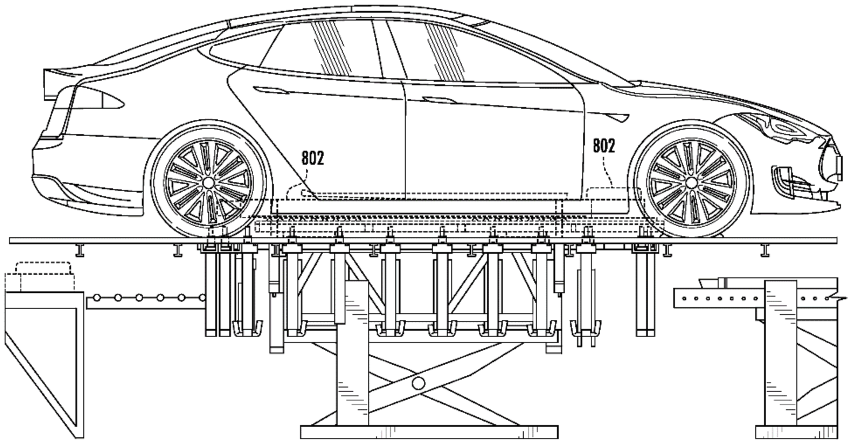


Figure 2.3 The sketch shows the new battery pack (802) positioned on top of the lift system and ready to be attached to the vehicle [13]

In the Figure 2.4 below there is the flow chart of the whole process required to remove and replace the batteries:

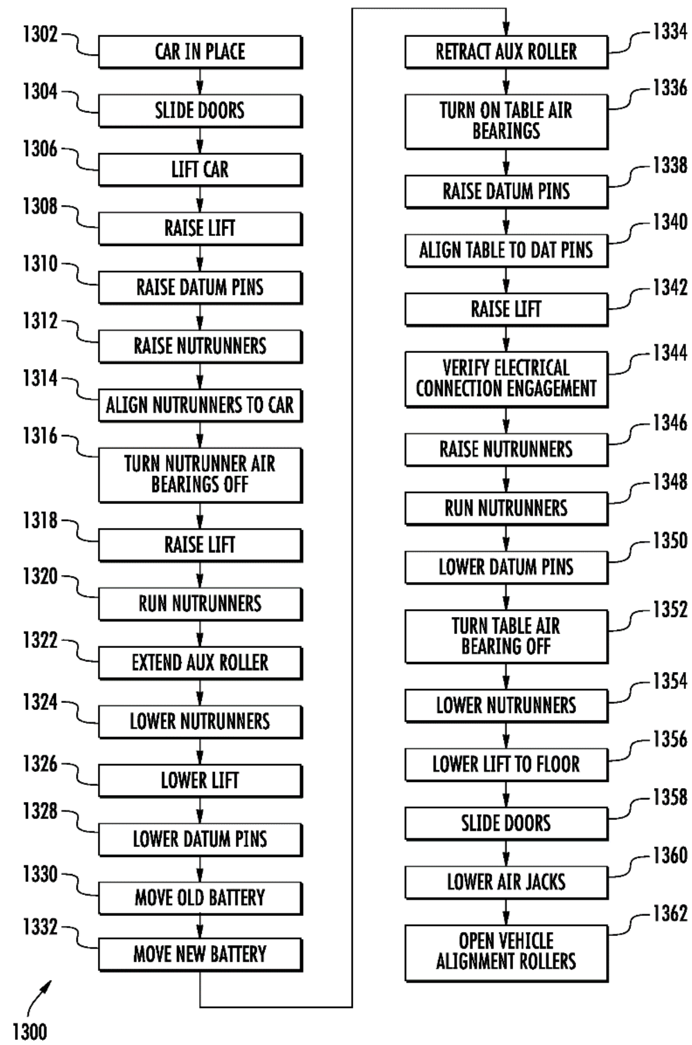


Figure 2.4 Procedure for swapping battery packs on electric vehicles [13]

Most of the researches in this field are mainly focused on energy management, allocation planning, optimal charging scheduling and decision-making problems, providing support for configuration plan of BSS.

Recent studies [14] and [15], have proposed a BSS scheduling model for the battery charging, according to the availability of battery chargers and hourly demand, to help the BSS owners in managing their resources and a BSS model to determine a charging schedule for electric buses minimizing energy cost and battery degradation, respectively.

An article disclosed on the journal "IEEE Transactions on Vehicular Technology" [16] focuses on a mathematical optimization model for charging depleted batteries at BSS whose purpose is to minimize its cost. In particular, the objective function to be minimized is based on three elements: the number of batteries taken from stock, the potential charging damage with different charging rates and the electricity cost. A sequence of simulation studies is then performed to assess the feasibility of the proposed model.

In [17], a new practical approach is suggested considering both the technical and socio-economic impacts. Based on the concept of BSS, a battery sharing station (BShS) as a part of a battery sharing network (BShN) is presented to improve the grid reliability and stability. A renewable energy source (RES) and a photovoltaics (PV) system are integrated with the BSS. In addition, a universal battery pack (UBP), that is linked through the IoT to optimize the cost of charging, reduces the waiting time for battery swaps and continuously manages the battery state of health (SOH), state of charge (SOC) and broadcasts its data with the BShS and the BShN, is proposed as an alternative to the traditional battery pack.

A closed-loop supply chain based on battery swapping-charging system (BSCS) is designed in [18] in order to realize the combined action of battery charging stations (BCSs) and battery swapping stations (BSSs) and at the same time ensuring the quality of the battery swapping service and maximizing the revenue of the BSCS. The optimization problem is formulated as a mixed-integer linear programming (MILP) problem and it is solved in a distributed way by decomposing the BSCS into subsystems.

Y. Zheng et al. [19], based on life cycle cost (LCC) criterion, have designed a method for locating and sizing BSSs in distribution systems to evaluate the cost/benefit of a BSS. The proposed model has been tested on IEEE 15-bus and 43-bus distribution network also considering the peak load in the system and the results demonstrate that the residential and light industrial areas are suitable for building BSSs, i.e. BSS is more suitable for public transportation in distribution systems.

Published in 2018, the work of T. Zhang et al. [20] proves that there are some special cases, such as taxi and bus fleets, in which, with a large number of EVs, battery swapping has better performance in terms of equivalent service capacity and profitability with respect to charging stations. They developed a stochastic model of buses, taxis, charging stations and battery swapping systems using Monte Carlo simulation and taking into account the impact of factors such as charging power, battery capacity, vehicle moving speed and swap price.

3 Scenario Definition

Once the current state-of-the-art implementations of the BSS have been discussed, through this paragraph, the modeling of a service station for battery swapping (called BSS) and a hypothesis of solution of use of this technology will be formulated as well as the model development process will be illustrated. Later, the validity and the effectiveness of the proposed model will be proof by a set of concrete scenarios.

3.1 Model Building

Given the context discussed above, the focus of this section is the development of a model for a BSS based on the configuration and discrete events modelling of a battery storage site to allow the management of EVs' battery using swap mode.
From the considerations made previously on the main characteristics of the EVs' battery packs (see Chapter 1 section 1.2), the purpose of this work is to evaluate the efficiency of the battery swap system through the design and simulation of a BSS model as realistic and accurate as possible in a scenario where EVs are a widespread resource. The city of Turin will be taken as a case study.

In order to consider both cars with standard range and with long range, it was decided to work with only two types of EVs and so two different types of battery packs. These battery packs belong to the two most sold electric cars in Italy in recent years (according to data taken from [21]): Renault Zoe R110 Z.E. 40 [22] and Tesla Model 3 Long Range [23]. The first battery pack have a capacity of 41 kWh while the second 75 kWh (see Figures 3.1 and 3.2).

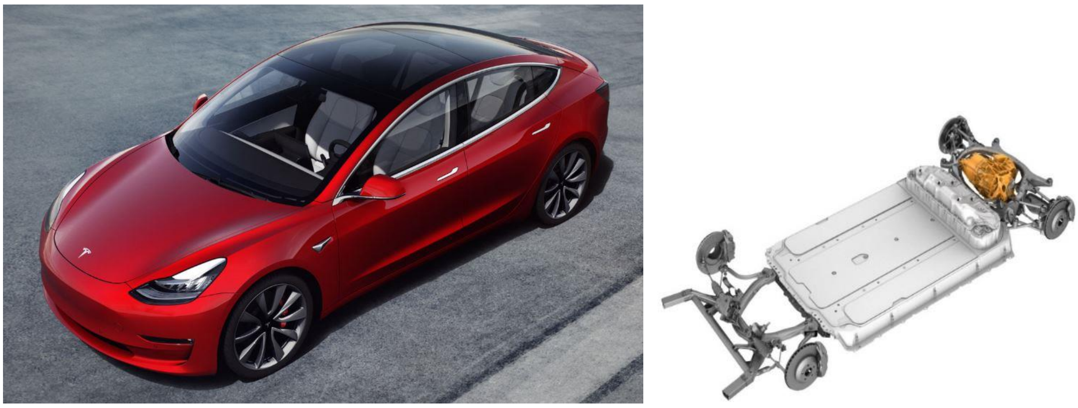


Figure 3.1 75 kWh Tesla Model 3 Long Range battery pack (Photo by Electrek)

Figure 3.2 41 kWh Renault Zoe R110 Z.E. 40 battery pack (Photo by Mark Kane)

The real range of these two types of cars varies depending on the combination of many variables including speed and driving style, topography (road conditions) and outside temperature (weather conditions). Nevertheless, the official test cycle WLTP[11] (World harmonized Light-duty vehicles Test Procedure) for Tesla Model 3 Long Range indicate a range of 348 miles (560 km) on a single charge in a mainly city environment with an efficiency of 13 kWh/100 km ([24] and [25]). As regards Renault Zoe R110 Z.E. 40 instead, according to the results obtained during the approval procedure WLTP, the range is 300 km under normal driving conditions with an efficiency of 14 kWh/100 km ([26] and [27]).
More in detail, the WLTP test is the evolution of the old European NEDC test whose values were based on theoretical driving profiles. This last has been designed in the 1980s and has now become obsolete due to technological evolution (just think about EVs) and changes in driving conditions (see Figures 3.3 and 3.4). Since the WLTP test gathers real-driving data, it better matches today's on-road performances and daily driving

[11] It provides fuel consumption and range data closer to actual than EPA (Environmental Protection Agency) or NEDC (New European Driving Cycle) procedures because the tests are carried out under more realistic and strict conditions

profiles. Therefore, the WLTP standard is an objective criterion for measuring differences in performance between the various models of different car manufacturers.

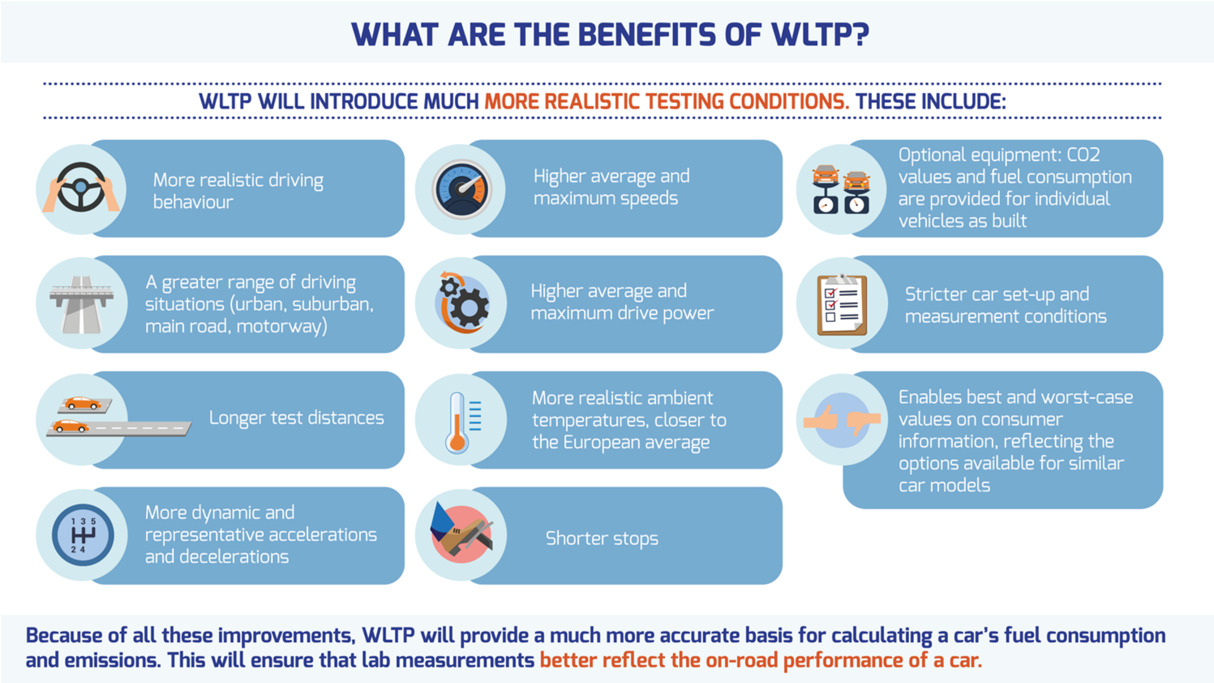


Figure 3.3 Benefits of WLTP test [28]

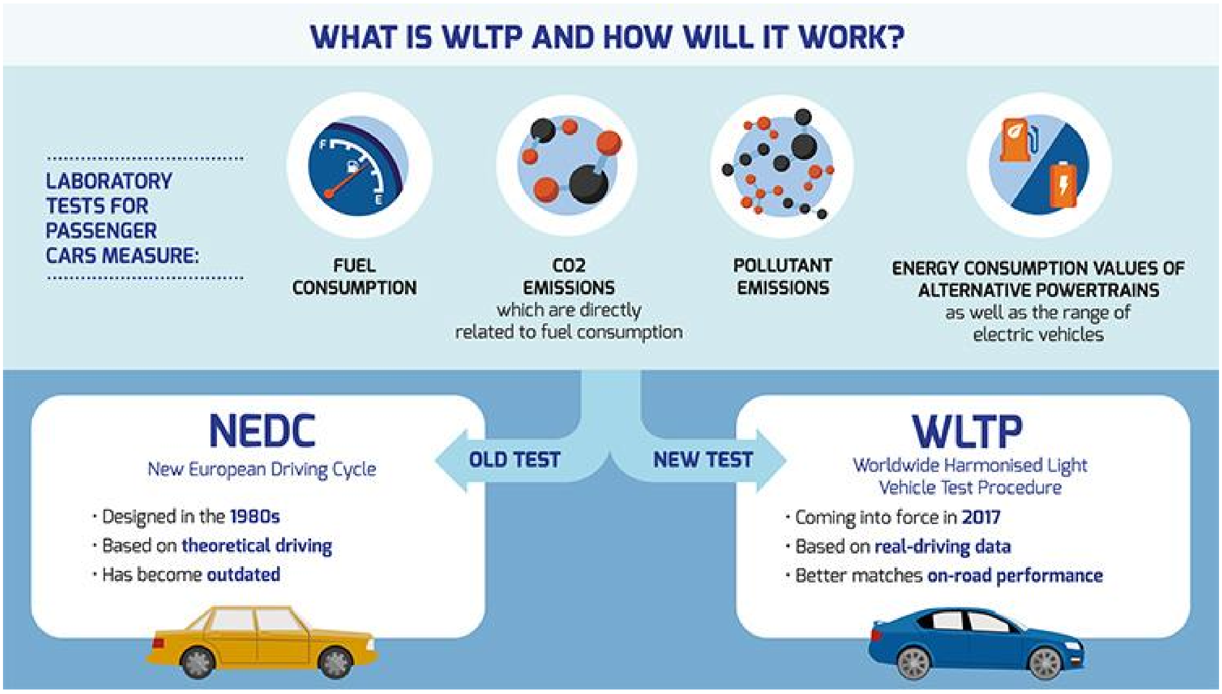


Figure 3.4 New CO2 emissions and fuel consumption test using WLTP [28]

In order both to predict daily battery swapping demand and to size the service station in the simulation model used, an analysis of the urban traffic of Turin of the vehicles on the road follows. Data on Turin city traffic flows have been provided by *5T Srl*, which

has developed and still manages the operational centre for real-time traffic monitoring and supervision (Traffic Operations Centre). Furthermore, 5T's measured data have a high reliability index since they were collected through a network of traffic sensors at fixed locations and using Floating Car Data technology, i.e. data from fleets of private vehicles in motion [29].
In Figures 3.5 and 3.6, it is possible to see the distribution of the number of vehicles circulating in Turin at different times of the day and the distribution of the number of kilometers travelled on the city network over 24 hours respectively[12].
It is important to underline that this represents an estimation of the total traffic in the city and the information obtained refers only to the vehicles measured by the sensors, which therefore do not represent all the vehicles circulating in the city.

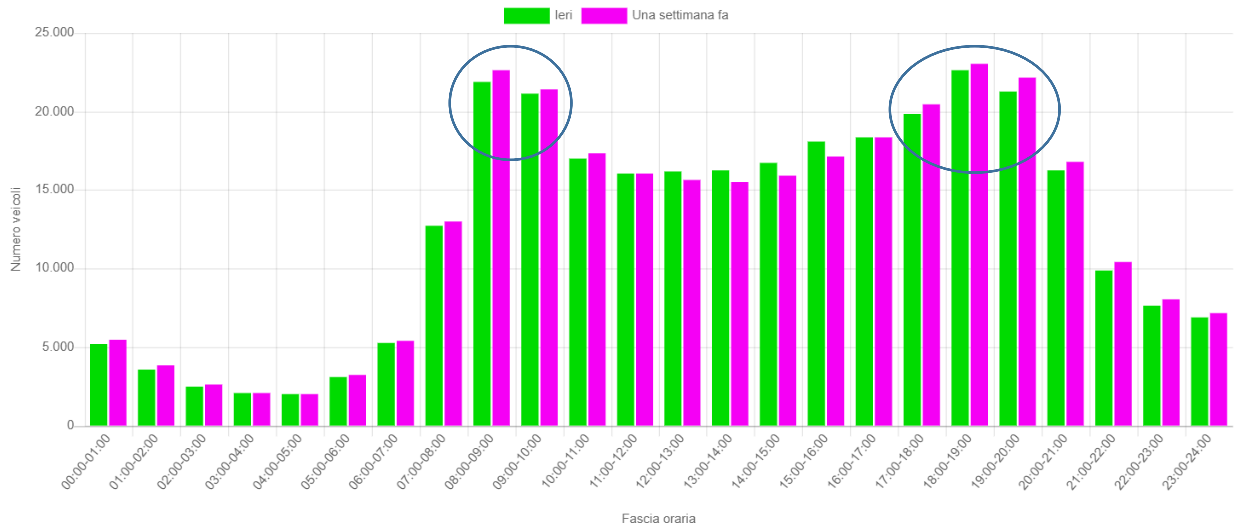


Figure 3.5 Vehicles Distribution on road in different time slots in Turin [30]

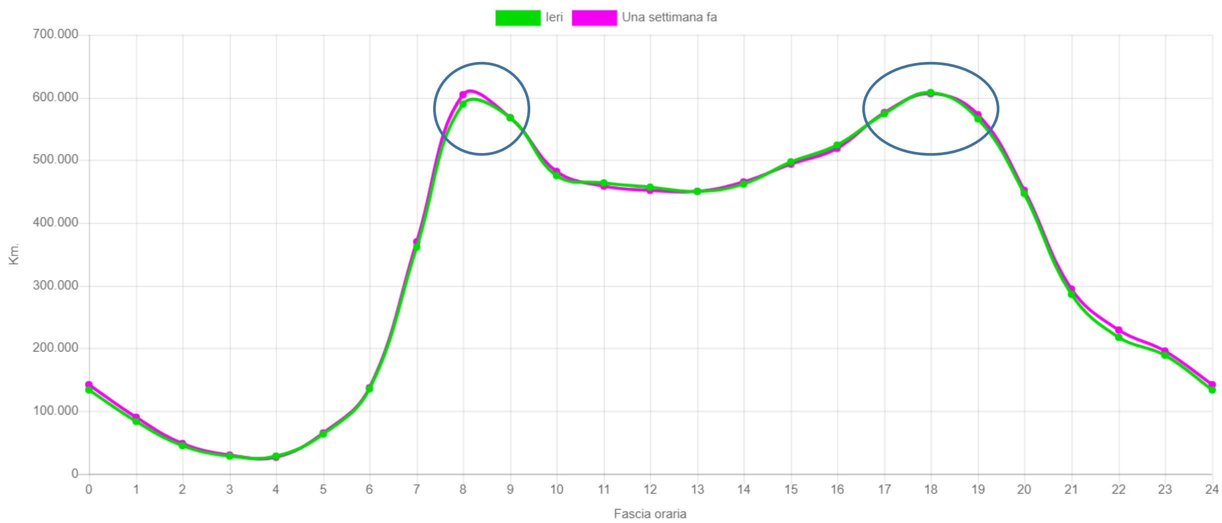


Figure 3.6 Kilometers Distribution covered by vehicles during time slots in Turin [30]

[12] Green part refers to Monday 28/10/19, while Purple part refers to 21/10/19.

By examining these distributions, the peak hours are from 08:00 to 09:00 in the morning and from 17:00 to 19:00 in the evening. No significant differences emerge between the distributions observed in other days of the week and the values are very similar to those shown in the figures 3.5 and 3.6.

From the data obtained, the total number of kilometers travelled each day is thus about 8 million, while the total number of vehicles in circulation is on average about 320 thousand, which represents roughly 44% of the total vehicle fleet in Turin (720 831[13]).
At this point, given both the kilometers travelled and the vehicles in circulation every hour, it is possible to derive the numbers of electric cars. Knowing that the car fleet in Turin is 576 571, which corresponds to 80% of the vehicle fleet, the same percentage has been used to estimate the number of cars in circulation every hour.
Assuming, in an ideal scenario, that all circulating cars are full electric and using only the two types of electric cars considered as well as their ranges, it is estimated on average the kilometers travelled by each car before recharging. Since Tesla Model 3's range is greater than that of the Renault Zoe, the entire electric cars fleet will be divided into 34% Tesla Model 3 and 66% Renault Zoe respectively. Afterwards, through a weighted average it is possible to know on average how many electric cars will need to recharge the battery every hour over a 24-hour period in the metropolitan city of Turin dividing the kilometers covered at each hour by the average kilometers travelled before recharging the EV's battery (see formula below).
At this point, given the large number of electric cars that may need to recharge the battery, the possibility of installing more battery swap stations in Turin to serve all electric cars will be considered.

To try to figure out what percentage of residual charge (SoC), i.e. the remaining battery capacity relative to its maximum capacity, electric cars could reach the station, a survey was carried out on a fairly disparate sample of 187 people focused on the behavior of electric car owners in relation to the charging need. The results of the study are indicated in Figure 3.7.

[13] Source: Tab III 28-29 from ACI (Automobile Club d'Italia) Statistical Yearbook 2019 data

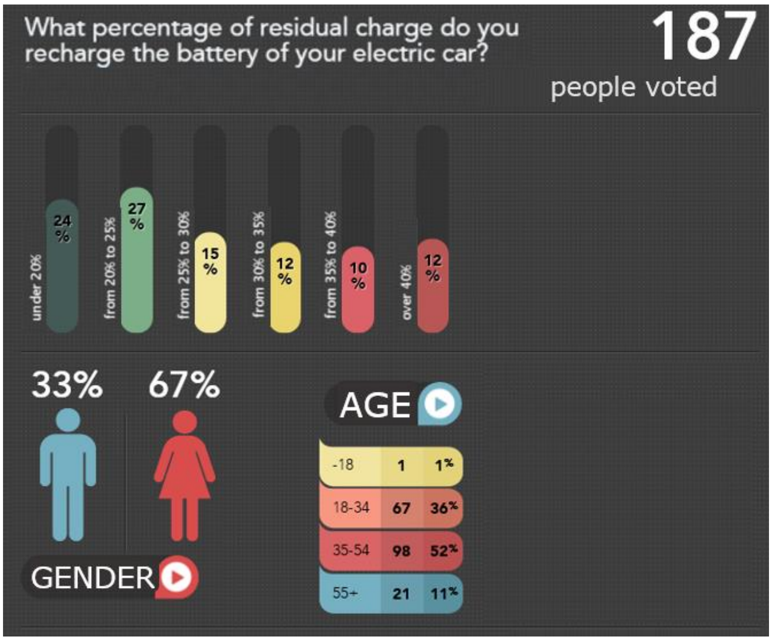


Figure 3.7 Survey on battery SoC levels to understand the drivers' behavior

As expected, the trend of the survey shows that there are both anxious and least demanding customer. Nevertheless, it is evident that more than half of the participants wait for their car's battery to reach the 25% of SoC before recharging it.
This study was also very useful for determining how many kilometers on average are covered before recharging the battery, because the higher the percentage of SoC, the less km the electric cars will travel on average and therefore the more cars will need to recharge the battery at the station.
Based on this information, it was decided to analyze, in addition to cases where the expected value of SoC is 20% and 25%, even the worst case in which cars arrive at the station with 30% of SoC's expected value in such a way as to stress the system and see how it reacts. Accordingly, it is assumed that the EVs' SoC arriving at the station are distributed according to a lognormal distribution, which reflects the survey result in Figure 3.7.

The criterion used to calculate the average kilometers travelled before recharging (KMT) is based on the assessment of the percentage of residual battery charge at the time of replacement (see the survey above), the distribution of the number of incoming cars according to the two types chosen and the range, in km, available at the time of recharging. This results in the following weighted average:

$$KMT = \%T * (RangeT * 0.9 - RangeT * ExpectedSoC) + \%R * (RangeR * 0.9 - RangeR * ExpectedSoC)^{14}$$

[14] The range is multiplied by 0.9 for the considerations made in Chapter 1 section 1.2

Where:

- %T = 34% -> is the percentage of distribution of Tesla Model 3 cars
- %R = 66% -> is the percentage of distribution of Renault Zoe cars
- RangeT = 560 km -> is the Tesla Model 3 range
- RangeR = 300 km -> is the Renault Zoe range
- ExpectedSoC = 20%, 25%, 30% -> variable parameter according to the above survey

Finally, to obtain an estimate of the hourly arrivals of the cars at the station, it is sufficient to divide the km travelled every hour (Figure 3.6) by the value just obtained (the results are shown in Chapter 4 section 4.6).

Lithium-ion batteries in electric cars can be recharged at any charge level (SoC), but they have a progressive performance decay that is accelerated by temperature changes and fast charging. As was pointed out earlier, charging times are also affected by the temperature of the external environment and the State of Health (SoH) of the battery, which represents the current condition of the battery, expressed as a percentage, with respect to its ideal conditions. On average, the life cycle of lithium-ion batteries is fixed at about 8 years or 1000 charging cycles. After a performance degradation of 20%, they must be replaced. In the figure below (Figure 3.8), the influence of temperature and fast charging on the life cycle of the Renault Zoe Z.E. 40 battery pack, made with 192 cells LG Chem E63, can be seen in detail.

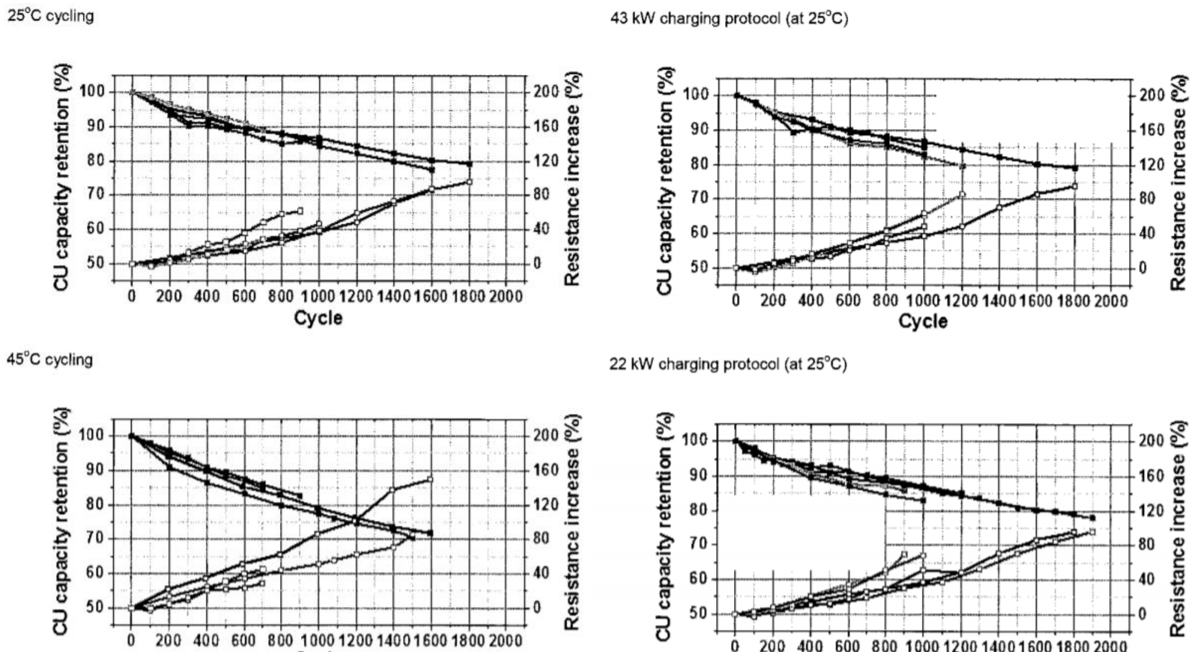


Figure 3.8 LG Chem E63 battery life cycle duration [31]

The loss of efficiency over time for the Renault Zoe battery based on temperature and cycles is evident: at 25°C, after 1400 cycles, the initial battery capacity drops to 80%, while at 45°C, only after 1000 cycles, the initial battery capacity drops to 78%. Same considerations will hold for fast charging: with a charging power of 43 kW after 1200 cycles the battery reach an efficiency level of 80% and using a power of 22 kW after 1600 cycles the battery efficiency is reduced by 20%.
Actually, the BSS must replace the battery packs when they reach an efficiency level of less than 80%, but this feature has not been implemented in this work because it is not part of the thesis goals.

In the BSS considered, a warehouse has the task of storing the exchanged batteries and at the same time charging them. The warehouse is designed to store a maximum of 60 battery packs[15] and the 60 chargers used, transform the alternating current into direct current before supplying the batteries. The charging time will depend on the factors already addressed in Chapter 1, section 1.2. The maximum charging power used by the chargers will be kept fixed at 22 kW (thus avoiding fast charges that could damage the batteries) and each battery pack will be recharged to a maximum SoC percentage of 90%, in line with what has already been discussed in sections 1.2 and 1.3.
It is important to clarify how the purpose of the model is not to make profit for example by selling electricity back to the grid through the discharging process of the batteries, also because this would lead to the reduction of the battery's lifecycle.

3.2 Model Assumptions

The stochastic model built involves the following assumptions that are applied to the scenarios created:

1. The model consider only private EVs
2. Since the station is automated, it is open 24 hours a day
3. The station can serve a maximum number of EVs equal to the number of battery swap workstations at a time

[15] This data have been provided by *Eurofork*, an Italian company located in the area of Turin (https://www.eurofork.com/it)

4. The battery packs for all incoming EVs can be of two different capacities and types, but of standard dimensions

5. The principle “first-in first-out” is used to serve EVs according to their arrival time

6. Each location in the warehouse is able to accommodate only one battery regardless of the type or the capacity of the latter

7. The number of battery chargers available is equal to the number of batteries the warehouse can hold

8. The battery's State Of Health (SoH) parameter will not be taken into consideration

9. No breakdown and recovery times for objects in the model has been considered

Moreover, to ensure that the temperature does not affect the battery charging time, it is assumed that in the warehouse there is an optimal temperature between 20 and 30 °C during both winter and summer [32]. The main system parameters used in the simulation model are summarized in the table below (Table 3.1):

Parameter		**Value**
RACK		
Rack Size (No. of items)	Bays Levels Cell Capacity	10 6 1
Total	(Maximum Content)	60
Rack Size (meters)	Width of Bays Height of Levels	2 1
No. of battery packs	Type 1 (41 kWh) Type 2 (75 kWh)	40 20
Total		60
No. of chargers		60
VEHICLES		
Task Executers Speed (m/s)	AGV (x-axis) ASRS (x-axis)	1 2

Task Executers Acceleration and Deceleration (m/s^2)	AGV ASRS	0.5 0.5
Load Times (s)	AGV ASRS	9 9
Unload Times (s)	AGV ASRS	9 9
Capacity	AGV ASRS	1 1
Lift Speed (m/s)	ASRS (z-axis)	0.23
Extension Speed (m/s)	ASRS (y-axis)	1.2
Initial Lift Height (m)	ASRS	3

Table 3.1 Summary of Parameters used in the Simulation Model

Both vehicles parameters and warehouse performances are fixed and are those provided today by the Eurofork company.

4 Methodology

The set of assumptions and estimation methods discussed in the previous chapter, now allow to develop the model for the Turin urban infrastructure. The creation of the model implemented is explained through the use of the simulation software FlexSim and will be discussed in this paragraph. The model allows to simulate the behavior of a BSS under various conditions with the presence of some configurable elements inside it. The stochastic behavior of the system considered as well as its performance will be also investigated.

4.1 Discrete Event Simulation

To reproduce the behavior of a real system, even complex, it is necessary to build an abstract simulation model, which allows both to define the relationships between the elements and the decisions to be taken and to trace all the operations carried out on the system and then predict its performance for the future. Simulation models can be classified into different types of models:

- *Continuous Models*: system in which the state variables change continuously over time
- *Discrete Models*: system where state variables change only at certain moments in time or when a specific event happen
- *Static Models*: in which a system is represented at a particular moment in time
- *Dynamic Models*: in which a system that evolves over time is represented
- *Deterministic Models*: system in which probability distributions are not taken into account
- *Stochastic Models*: system in which there are elements subject to randomness

All those types of simulation models that are *discrete*, *dynamic* and *stochastic* are commonly called *Discrete-Event Simulation models* (see Figure 4.1) and are particularly used in many applications such as software systems for higher-level automation of plants

and industrial processes, to study the temporal evolution and approximate the behavior of continuous systems.
Discrete event simulation (DES) is the process of codifying the behavior of a complex system as an ordered sequence of well-defined events. In this context, an event comprises a specific change in the system's state at a specific point in time [33].
In a discrete-event model the system is characterized in every moment of time by a set of variables called state variables, by events that modify the value of at least one of the state variables, by entities (single elements of the system) and their attributes, by resources and by activities (operations of known duration) and delays.

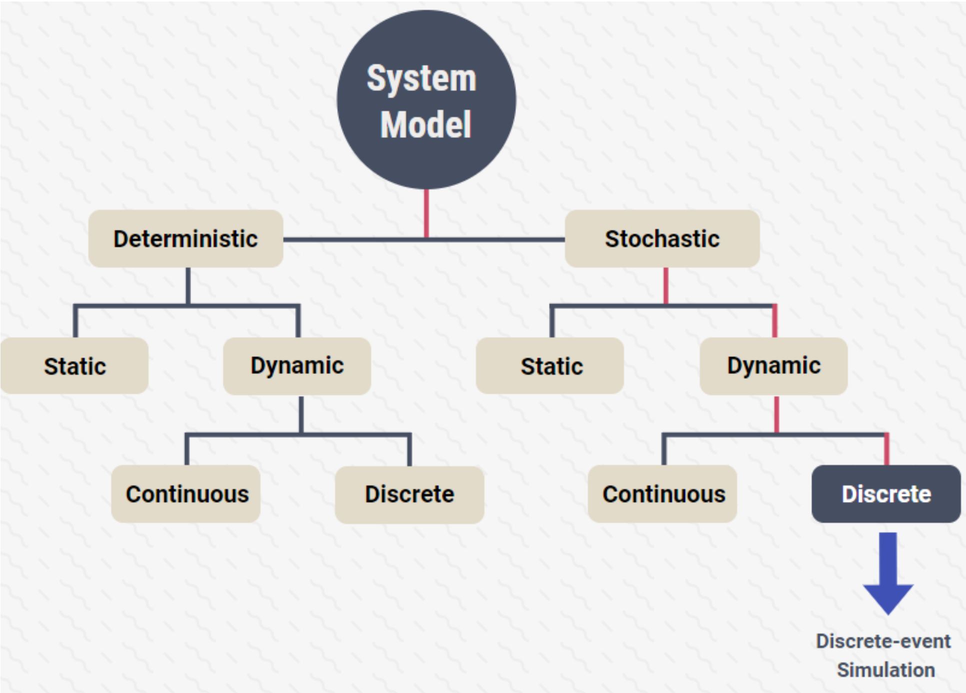


Figure 4.1 Model taxonomy for systems

4.2 Simulation Software

From this perspective, among several commercial DES software that perform manufacturing simulations (see Table 4.1), *FlexSim* has been chosen to visualize, analyze and improve in a more concrete way the behavior of the considered system for real-world processes and applications. Thanks to *FlexSim*, it was possible to easily create the simulation model and achieve the final goal of this analysis, which is to better understand what conditions and processes optimize the BSS system as well as the advantages and disadvantages that a company can derive from its implementation.

FlexSim is 3D simulation software that models, simulates, predicts, and visualizes business systems in a variety of industries: manufacturing, material handling, healthcare, warehousing, mining, logistics, and more [34].

FlexSim is a powerful yet easy-to-use software package that implements a C-like language called FlexScript and it has been designed with an open architecture to integrate with C++ as well (see Figure 4.2). The main features of this simulation software comprise the use of [34]:

1. A highly realistic 3D graphics simulation to see any actions that occur during the simulation and to confirm whether the system is working or not as it was intended to (visual validation)

2. A model layout that exploits drag-and-drop controls to arrange resources and 3D objects used in model building directly into the 3D environment

3. A model building with:
   I. a standard object library set and a drop-down lists to customize objects, events, functionalities and system properties
   II. a process flow using activity blocks to build system logic

4. A full suite of analysis features that includes a list of graphical interfaces, predefined or customized by the user, called dashboards to better visualize data of interest from running simulation and the possibility of collecting and exporting data to other calculation applications like Excel spreadsheet (statistical validation)

5. Two optimization tools (Experimenter & Optimizer) in order to simulate multiple scenarios in which input variables and performance indicators are different, make the best possible choices and compare the results of the solutions

Figure 4.2 FlexSim 3D virtual environment

Number of stars	Significance
*	Inadequate
**	Adequate
***	Satisfactory
****	Very satisfactory
*****	Outstanding

Criteria Groups	Comparison Criteria	Simulation Software Tools AnyLogic	Arena	Flexsim	Plant Simulation	Witness
Hardware and Software	Coding aspects	****	***	**	****	**
	Software compatibility	***	**	***	****	***
	User support	****	**	****	****	***
General features	Purpose	General	General	General	General	General
	Experience required	***	****	**	***	**
	Ease of use	***	**	**	***	****
Modelling assistance	On-line help	****	**	****	***	**
	Library and templates	***	**	****	****	***
	Comprehensiveness of prompting	***	**	***	***	***
Simulation capabilities	Visual aspects	****	**	*****	****	***
	Efficiency	****	**	****	****	***
	Testability	****	***	****	****	***
	Experimentation facilities	***	***	****	****	***
Input / Output	Statistical data	****	***	****	****	****
	Input/output capabilities	****	***	****	*****	****
	Manufacturing capabilities	****	**	****	****	*****
	Analysis capabilities	***	***	****	****	***

Table 4.1 Rating scale & comparative matrix of the most used commercial simulation tools [35]

All these functionalities make this software very complete, allowing to easily control and modify the simulation model from multiple perspectives.
In this thesis work, the most stable version of FlexSim has been used (version 19.0.0 for 64-bit built on 03/01/19).

Taking into account the potentialities of FlexSim discussed above, a description more in-depth of the virtual environment follows.

4.3 FlexSim Environment

The FlexSim user interface is divided into several box, as shown in Figure 4.3, which interact with each other:

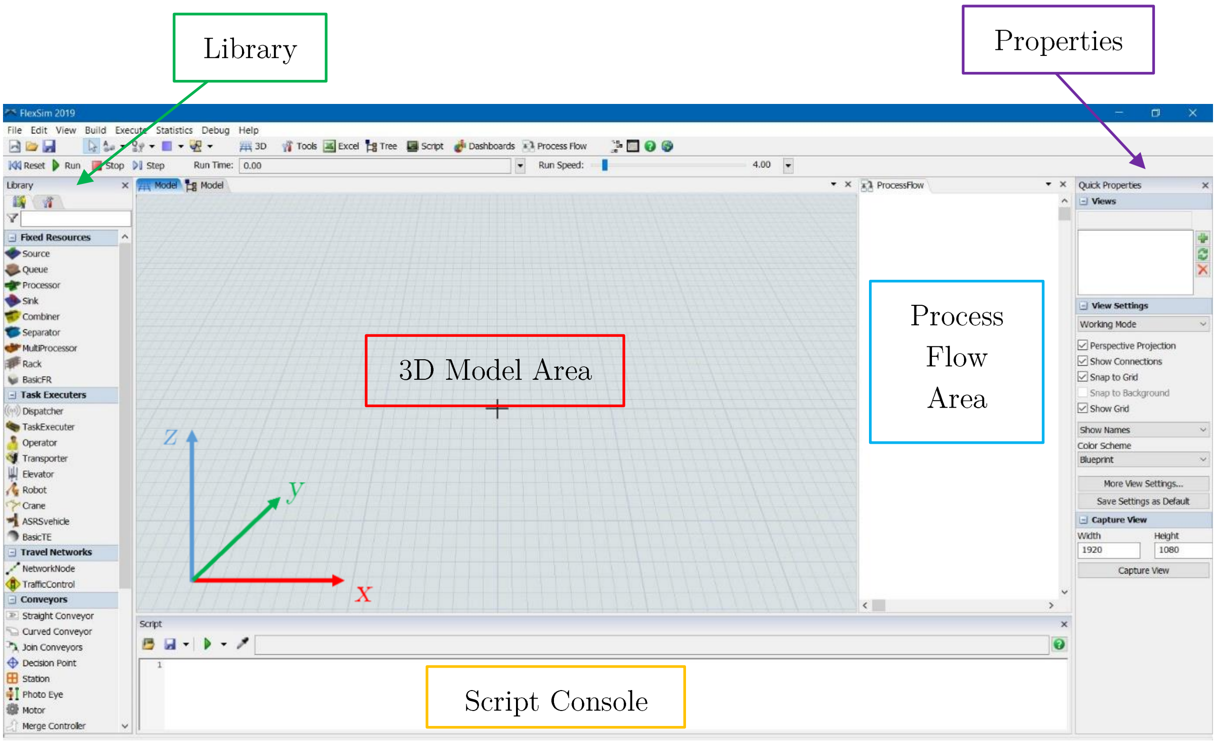


Figure 4.3 FlexSim Main Screen

The 3D model area is located in the center panel in FlexSim, the library (and the toolbox) in the left panel, the properties and the process flow view in the right side and the script console in the bottom panel. In the FlexSim reference system, the x-axis (in red) corresponds to the horizontal axis, the z-axis (in blue) coincides with the vertical axis and the y-axis (in green) represents the depth. On these axes task executers (like AGV and ASRS) can travel.

The 3D model field, that is the main workspace, is where, by means of animations and 3D graphics, the whole system is visualized and validated. The library includes all the objects, divided into categories or classes that have a high level of customization and can be used to both build the 3D simulation model and to create activity blocks in the process flow (see Figures 4.4 and 4.5). In the properties section, the most important details (features, values, labels, etc.) about the objects present in the simulation model are given. The script window is useful to execute FlexScript code in order to obtain information or configure the simulation model without running the model. Moreover, in the script console the code can be debugged. Lastly, there is the process flow interface that allows to create and to build the overall logic of the simulation system that is the basis of the operation of the simulation model.

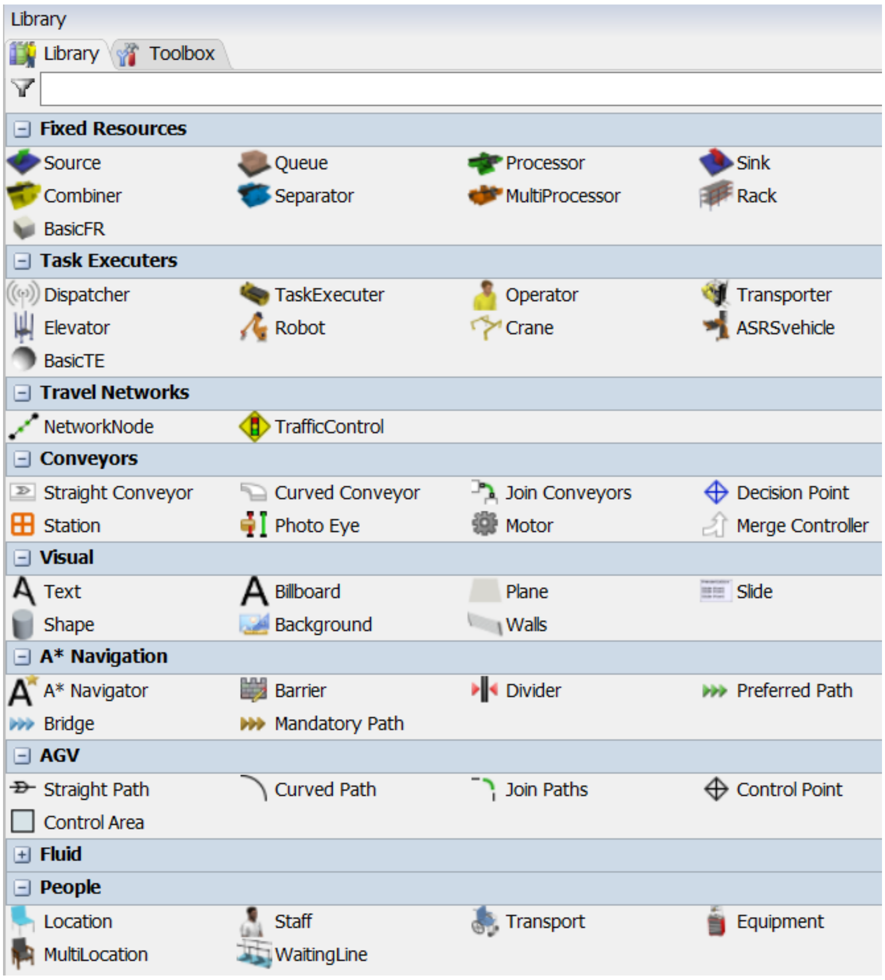


Figure 4.4 FlexSim Objects Library

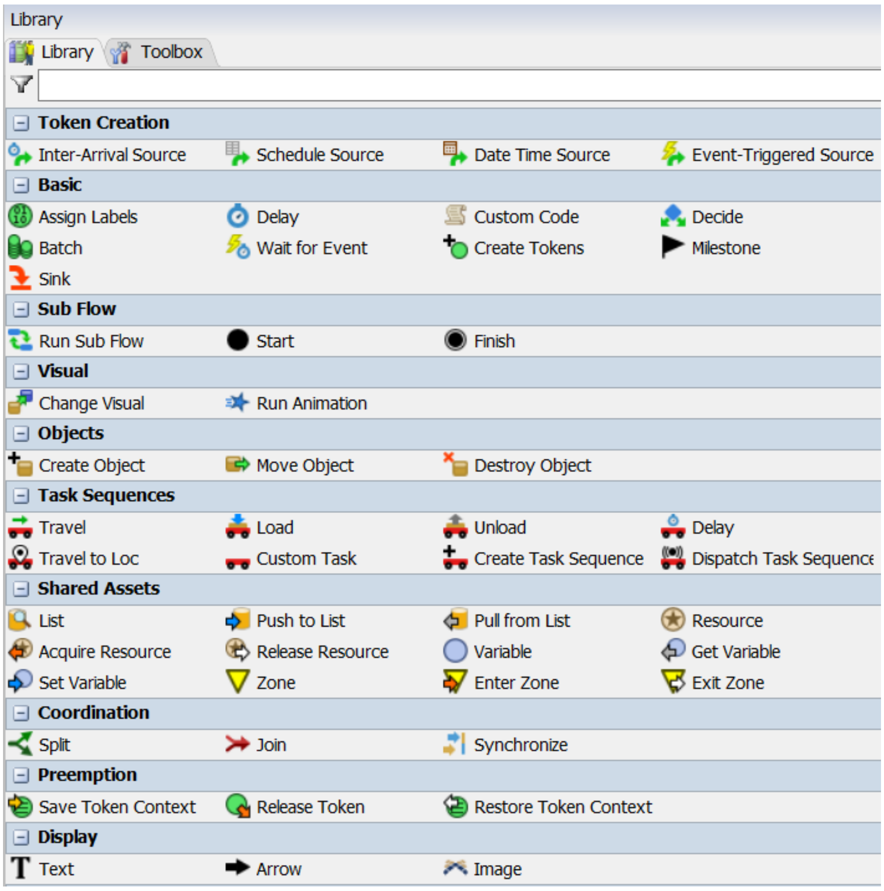


Figure 4.5 FlexSim Process Flow Library

The process flow tool has a flow chart-like visuals where is possible to create blocks that represent tasks, activities or resources. The main elements of a process flow are tokens, activities and shared assets. Tokens represent the simulation status and are essentially flow items moving from one activity to the next. Moreover, they are specified by a green circle and identify the position and activity that the item should perform in the model. Each token contains basic information such as ID, name and labels in order to identify and store custom data.

Tokens in this model are associated with battery packs in such a way that, by tracking token information, it is possible to keep track of every battery pack in the system.

Activities are the logical operations in the process flow and are linked to each other with connectors. A set of activities can be grouped together into a single stacked block creating sequence of steps.

Shared assets are essentially limited resources that tokens can release or claim at specific points in the process flow. Whenever a shared asset is unavailable, the token that requests it has to wait for that resource to become available in order to move on to the next activity. Shared assets can be of three different types including resources, lists and zones, which correspond to limited supply of resources, lists and statistical information respectively.

4.4 Development of the Simulation Model

The model developed consists of two main parts. First, all necessary simulation objects with their connections, corresponding parameters, labels and initial values have been created directly in the 3D model area. After that, it still be possible to make manual changes to the model in order to simulate and test situations that are even more complex. In the second part, the model created in this way is then handled through a process flow in which the rules of operation of the system are collected. Most of the values or parameters assigned to objects in the model are not fixed and can be changed in the simulation in order to make the model as flexible as possible for future changes. For this reason, several of the customizable parameters in the model have been saved as global variables. Among these, there are the maximum battery charge level, expressed as a percentage, in the rack (*MaxLevelRackSoC*); the SoC update rate for the batteries in the warehouse (*UpdatingTime*); the time required to remove the battery or insert it into the car (*DelayTime*); and the time it takes a customer to leave the station once served (*DepartureTime*). In this paragraph, the general layout of the model is outlined, highlighting all the objects involved.

It must be noted that, since it is not possible to draw on a precise reference plant layout of the station, the distances and paths between objects may change. In this model, the flow items will represent batteries that enter the BSS. Looking at Figure 4.10, at the end of this section, six types of objects, made available by the software, can be identified in the model and each of them is described in the next pages:

1. Two Sources (Fixed Resource) to generate the incoming battery packs during runtime (*SourceBattery*) and the battery packs available in the rack at startup (*SourceRack*)
2. Two Queue (Fixed Resource) to model the customers' waiting queue (*WaitingQueue*) and the battery swap bay (*SwapBay*) where the AGV exchanges the discharged battery for a charge, and two more queue for storage (*StoringBay*) and retrieval (*RetrievalBay*) operations
3. A Sink (Fixed Resource) to represents the customers' exit from the station (*OutBattery*)
4. An AGV (Automated Guided Vehicle) & an ASRS (Automated Storage and Retrieval System) Vehicle (Task Executer) for transporting and moving batteries

5. A Rack (Fixed Resource) to store and charge the battery packs (*BatteryWarehouse*)
6. An AGV network (AGV) to provide a set of paths that will be followed by the vehicle

The Sources:

The *SourceBattery* is the object that generates the incoming items that enter the station, i.e. the batteries to be swapped. In the properties tab, the Arrival Style can be parametrized with an inter-arrival time, an arrival schedule or with an arrival sequence. In this model, the first method was chosen because it allows to better represent customers (and so batteries) coming to the BSS. Since the source will determine how frequently batteries arrive, for the same reasoning as in Chapter 3 section 3.1, the arrival rate was modelled through "Hourly Rates, Custom Daily Repeat" which allows to specify the arrivals at each hour in a day (Figure 4.6).

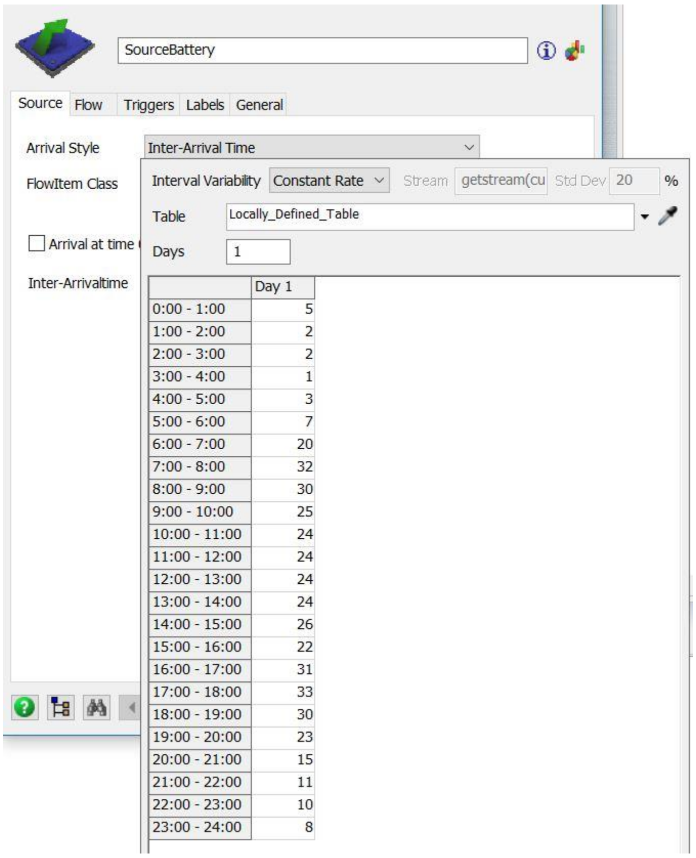


Figure 4.6 Example of battery hourly rates in a day

When an item is created from this source, the *On Creation Trigger* is executed and it has the purpose of assigning all the labels necessary to uniquely identify the battery.

These labels include the battery *Type*, the battery *Capacity* (expressed in kWh), the battery *State of Charge* (expressed in percentage), the *State*, the *MaxSoCTime* and a binary label called *ToSwap* set to one to indicate that the battery should be exchanged. Moreover, in the 3D model, to visually underline the different types of batteries, the item's color appearance is changed based on battery Type (Type 1 in red and Type 2 in green). The *On Creation Trigger* code, written in FlexScript language, is shown below:

```
// On Creation Trigger
Object current = ownerobject(c);
Object item = param(1);
int rownumber = param(2); //row number of the schedule/sequence table

{ // ************* PickOption Start ************* //
/***popup:SetLabel*/
/**Set Label*/
Object involved = /** \nObject: **/ item;
string labelname = /** \nLabel: **/ "Type";
Variant value = /** \nValue: **/ bernoulli(66, 1, 2, getstream(current));

involved.labels.assert(labelname).value = value;
} // ******* PickOption End ******* //

{ // ************* PickOption Start ************* //
/***popup:SetLabel*/
/**Set Label*/
Object involved = /** \nObject: **/ item;
string labelname = /** \nLabel: **/ SoC";
Variant value = /** \nValue: **/ lognormalmeanstdev(25, 25, getstream(current));

involved.labels.assert(labelname).value = value;
} // ******* PickOption End ******* //

{ // ************* PickOption Start ************* //
/***popup:SetLabel*/
/**Set Label*/
Object involved = /** \nObject: **/ item;
string labelname = /** \nLabel: **/ "ToSwap";
Variant value = /** \nValue: **/ 1;

involved.labels.assert(labelname).value = value;
} // ******* PickOption End ******* //

{ // ************* PickOption Start ************* //
/***popup:SetObjectColor*/
/**Set Object Color*/
Object object = /** \nObject: **/ item;
object.color = /** \nColor: **/ Color.byNumber(item.Type);
} // ******* PickOption End ******* //

{ // ************* PickOption Start ************* //
/***popup:SetLabel*/
/**Set Label*/
Object involved = /** \nObject: **/ item;
string labelname = /** \nLabel: **/ "Capacity";

Array vetttipo = Table.query("SELECT ARRAY_AGG(Type) FROM TypeTable")[1][1];
Array vettcap = Table.query("SELECT ARRAY_AGG(Capacity) FROM TypeTable")[1][1];

for (int i=1; i<= numType; i++){
             if (item.Type == vetttipo[i])
                    involved.labels.assert(labelname).value = vettcap[i];
}
} // ******* PickOption End ******* //
```

```
{ // ************* PickOption Start ************* //
/***popup:SetName*/
/**Set Name*/
treenode involved = /** \nObject: **/ item;
string name = /** \nName: **/ "Battery " + string.fromNum(nameBattery+1);

involved.name = name;
nameBattery++;
} // ******* PickOption End ******* //
{ // ************* PickOption Start ************* //
/***popup:SetLabel*/
/**Set Label*/
Object involved = /** \nObject: **/ item;
string labelname = /** \nLabel: **/ "State";
Variant value = /** \nValue: **/ 1;

involved.labels.assert(labelname).value = value;
} // ******* PickOption End ******* //
{ // ************* PickOption Start ************* //
/***popup:SetLabel*/
/**Set Label*/
Object involved = /** \nObject: **/ item;
string labelname = /** \nLabel: **/ "MaxSoCTime";
Variant value = /** \nValue: **/ -1;

involved.labels.assert(labelname).value = value;
} // ******* PickOption End ******* //
```

As it can be seen from the code reported above, the value assigned to *SoC* label varies according to a lognormal statistical distribution (consistent with what is indicated in the survey in Chapter 3 section 3.1) that follows the pattern shown in Figure 4.7 with standard deviation equal to the mean. The *Type* label follows a Bernoulli distribution: in that way 66% of the batteries generated will be of Type 1 (41 kWh) and 34% of Type 2 (75 kWh). This means that on the total number of EVs arriving at the station, about $\frac{1}{3}$ will be Tesla and $\frac{2}{3}$ Renault.

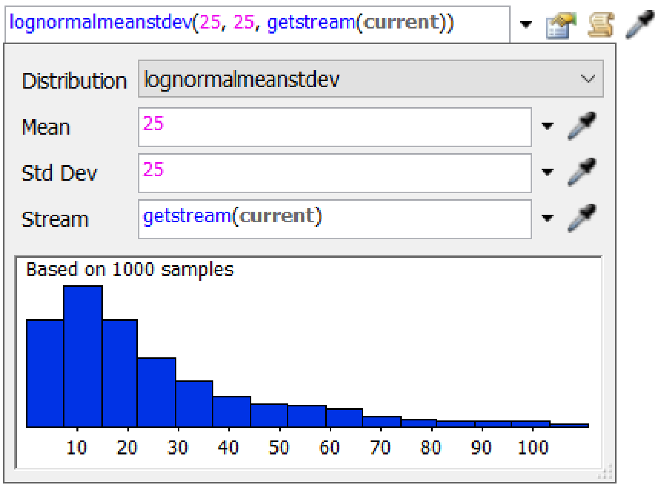
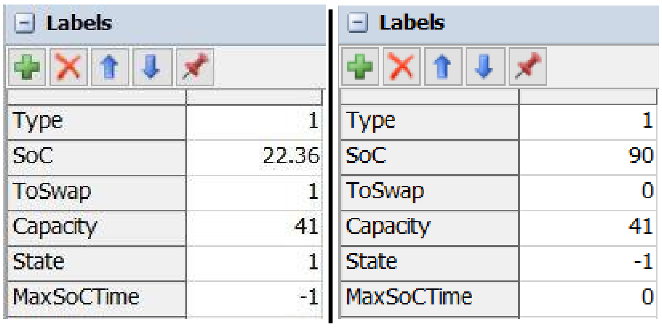


Figure 4.7 Example of lognormal distribution with mean 25 and Std. Dev. 25

The *SourceRack* instead is responsible for generating the batteries inside the warehouse at the beginning of the simulation. In this case, a single arrival schedule has been chosen

with a quantity equal to the maximum content of the rack. Basically, this object assigns the same labels to the batteries as described above for the *SourceBattery*, but with a different *SoC*, equal to the global variable *MaxLevelRackSoC*, *State* and *MaxSoCTime*. The *ToSwap* label is set to zero indicating that the batteries in the warehouse should not be exchanged.
In Figure 4.8 it can be seen, on the left, the items labels properties generated by the source *SourceBattery* and on the right the items labels properties created by the source *SourceRack* and placed in the warehouse.



Labels		Labels	
Type	1	Type	1
SoC	22.36	SoC	90
ToSwap	1	ToSwap	0
Capacity	41	Capacity	41
State	1	State	-1
MaxSoCTime	-1	MaxSoCTime	0

Figure 4.8 Example of item's labels generated by the two sources

The Queues:

The *WaitingQueue* represent a queue where customers will wait for their turn. In its properties tab, especially in Output section, the items are pushed to a global list called *WaitingBattery*. In this way, when batteries enter the *WaitingQueue*, they will be added to a list of waiting batteries, which will track useful information including how long batteries, and so customers, have been waiting. The "Reevaluate Sendto on Downstream Availability" box is checked in order to consider to push to list every time a downstream object becomes available. The output logic of this queue is set to FIFO (First in First Out). The *OnEntry* and *OnExit Triggers* are needed to store items' time references.

SwapBay is the workstation where the battery swap takes place. Its maximum content is set to one since the station can serve one customer at a time. In the Input group of the flow tab, the pull strategy checkbox is selected because it should pull from *WaitingBattery* list the battery that has been waiting the longest first so that following FIFO strategy as explained before. This queue has a binary label called *Busy* that is used essentially to engage the queue during the entire battery swap procedure and to not allow other batteries, waiting to be served, to enter. Every time an item enters in this object from the *WaitingQueue*, the *OnEntry Trigger* is activated and the *Busy* label is set to one.

In the *StoringBay* the AGV drops off the item, i.e. the depleted battery, and thus simultaneously the *ToSwap* label of the item is changed to zero because the battery has been swapped and will be stored in the rack, by means of the ASRS, where it will be charged. The *RetrievalBay* is where the ASRS places the charged battery retrieved from the rack that will be picked up by the AGV.

The Sink:

The *OutBattery* object is used to destroy items from the simulation model, so this sink represent customers leaving the BSS. When this happens, the *OnEntry Trigger* is activated and the label of the *SwapBay* is set to zero to allow the next waiting battery to enter the workstation. In addition, to keep track of all destroyed batteries, two global tables called *BatteryTable* and *CustomersTable* are filled, in which in each row data of both battery and customer leaving the station are stored. Follows the code of the *OnEntry* Trigger.

```
// On Entry Trigger
/**Custom Code*/
Object current = ownerobject(c);
Object item = param(1);
int port = param(2);

Object obj = model().find("SwapBay");
obj.labels.assert("Busy").value = 0;

Table table = Table("BatteryTable");
Table table1 = Table("CustomersTable");
int riga = current.labels["Exit"].value;

// Update CustomersTable
table1.addRow(riga);
table1.setRowHeader(riga,"Customer " + string.fromNum(numCustomer));
table1.cell(riga,1).value = item.StartWait;
table1.cell(riga,2).value = item.EndWait;
table1.cell(riga,3).value = item.StartService;
table1.cell(riga,4).value = item.EndService;
table1.cell(riga,5).value = item.EndWait-item.StartWait;
table1.cell(riga,6).value = item.EndService-item.StartService;
table1.cell(riga,7).value = table1.cell(riga,5).value + table1.cell(riga,6).value;

numCustomer++;
```

```
// Update BatteryTable
table.addRow(riga);
table.setRowHeader(riga,"Battery " + string.fromNum(numBattery));
table.cell(riga,1).value = item.Type;
table.cell(riga,2).value = item.Capacity;
table.cell(riga,3).value = item.StoringSoC;
table.cell(riga,4).value = item.SoC;
table.cell(riga,5).value = item.EntryTime;
table.cell(riga,6).value = item.MaxSoCTime;
table.cell(riga,7).value = item.OutTime;
table.cell(riga,8).value = item.State;
table.cell(riga,9).value = item.Energy;
table.cell(riga,10).value = item.OutTime-item.EntryTime;

if (item.MaxSoCTime != -1){
       table.cell(riga,11).value = item.OutTime-item.MaxSoCTime;
       table.cell(riga,12).value = item.MaxSoCTime-item.EntryTime;
}
else{
       table.cell(riga,11).value = 0;
       table.cell(riga,12).value = item.OutTime-item.EntryTime;
}

numBattery++;
current.labels.assert("Exit").value+= 1;
```

The Vehicles:

The two task executers used in the model are the AGV and the ASRS vehicle. The first is responsible for moving items from the *SwapBay* to the *StoringBay* and back from the *RetrievalBay* to the *SwapBay* along its own x-axis. The most important parameters to be set are the acceleration and the maximum speed as well as the loading and unloading times. Its task sequence is described in the Process Flow in the next paragraph. The second task executer is responsible for batteries storage (*StoringBay*) and retrieval (*RetrievalBay*). This vehicle has significant parameters to take into consideration, which include lift speed, extension speed, max speed, acceleration & deceleration as well as time for loading and unloading operation. The values of the most important parameters assigned to these two vehicles are listed in Table 3.1 Chapter 3 section 3.2.

The Rack:

The *BatteryWarehouse* object is the main element of the model because it is not only the place where the batteries are stored and picked up, but also where they are recharged. It is initially filled with 60 charged batteries (40 of Type 1 and 20 of Type 2 to maintain the proportions 66% and 34% respectively) placing the incoming items in a random bay and level. After a series of simulations, it has been observed that the optimal configuration for the warehouse, which allows to reduce the operations times for the 60 batteries stocked, is that one constituted by 6 bays and 10 levels. Every time an item enters the rack, the *OnEntry Trigger* is executed: this assign to each item in the rack a label to store the time it enters (*EntryTime*) and a label to store the SoC in order to compute the batteries level of charge (*StoredSoC*). Moreover, the entering items are pushed to the global list *BatteryRack* that stores all relevant information about batteries in the rack. The *OnExit Trigger* stores in the items the labels relating to the energy used by the station during charging (*Energy*) and the time when the item is picked up from the warehouse (*OutTime*).

Each item is assigned a label called *State* to distinguish the batteries inserted in the warehouse at the beginning of the simulation, those that have reached the maximum charge and finally those who are charging. This label has been inserted to first provide the charged batteries already in the warehouse, then the swapped batteries that have reached the maximum SoC and lastly those that have reached the highest SoC. When a battery achieved its maximum charge, its label switches from one state to another as illustrates in Figure 4.9.

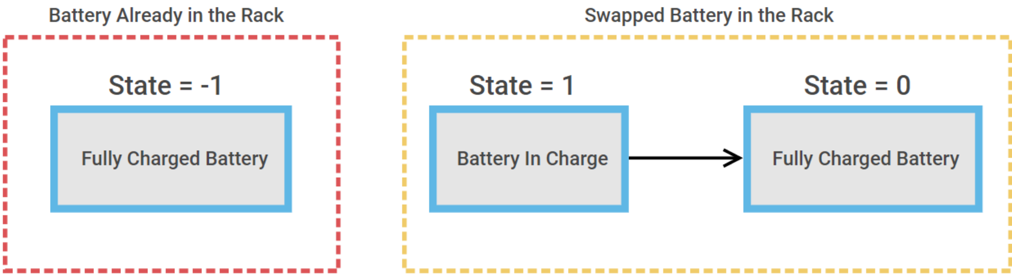


Figure 4.9 Battery State label transitions

In this way, the retrieval logic of the batteries to be picked up from the warehouse will follow a priority order given by the descending *State* label: State = -1; State = 0 and State = 1 (see next section).
Figure 4.10 shows the model side and top view with all the objects created (the batteries of Type 1 are red, while those of Type 2 are green).

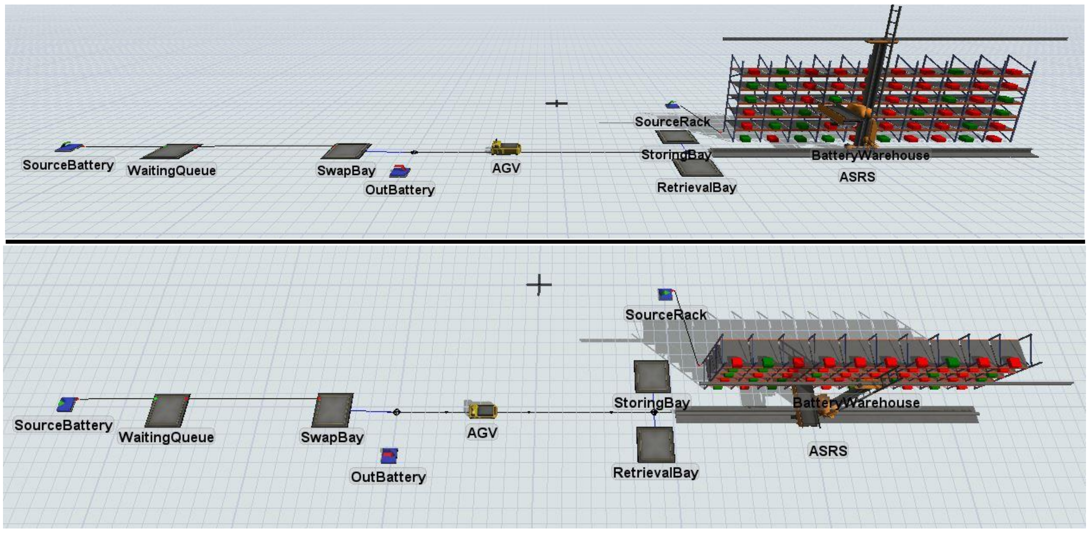


Figure 4.10 Model created in FlexSim

When the model is reset, i.e. before starting the simulation run, The *OnModelReset Trigger* is executed: this is useful to initialize and set all global tables to their starting values. The *OnModelReset* code is presented below:

```
// On Reset Code
/* Reset Code */
Object obj = model().find("BatteryWarehouse");

// Reset TypeTable
Table table = Table("TypeTable");
table.clear();
table.setColHeader(1, "Type");
table.setColHeader(2, "Capacity");
table.setSize(2, 2);
int tip = 1;
int cap = 41;

for (int i=1; i<=2; i++){
       table.cell(i,1).value = tip;
       table.cell(i,2).value = cap;
       tip++;
       cap+=34;
}

// Reset BatteryTable
Table table1 = Table("BatteryTable");
table1.clear();
table1.setSize(0,12);
table1.setColHeader(1, "Type");
table1.setColHeader(2, "Capacity");
table1.setColHeader(3, "StoringSoC");
table1.setColHeader(4, "SoC");
table1.setColHeader(5, "EntryTime");
table1.setColHeader(6, "MaxSoCTime");
table1.setColHeader(7, "OutTime");
table1.setColHeader(8, "State");
table1.setColHeader(9, "Energy");
table1.setColHeader(10, "StayTime");
table1.setColHeader(11, "StayTimeToMax");
table1.setColHeader(12, "ChargingTime");

// Reset CustomersTable
Table table0 = Table("CustomersTable");
table0.clear();
table0.setSize(0,7);
table0.setColHeader(1, "StartWait");
table0.setColHeader(2, "EndWait");
table0.setColHeader(3, "StartService");
table0.setColHeader(4, "EndService");
table0.setColHeader(5, "TimeOfWait");
table0.setColHeader(6, "TimeOfService");
table0.setColHeader(7, "TimeInStation");
```

```
// Reset WaitTable & PowerTable
Table table2 = Table("WaitTable");
Table table3 = Table("PowerTable");
table2.clear();
int bay = rackgetnrofbays(obj);
int level = rackgetnroflevels(obj);
table2.setSize(level,bay);
table3.setSize(level,bay);

int dimension1 = 1;
for (int i=1; i<=level; i++){
	table2.setRowHeader(i, "Level " + string.fromNum(dimension1));
	table3.setRowHeader(i, "Level " + string.fromNum(dimension1));
	dimension1++;
}

int dimension2 = 1;
for (int i=1; i<=bay; i++){
	table2.setColHeader(i, "Bay " + string.fromNum(dimension2));
	table3.setColHeader(i, "Bay " + string.fromNum(dimension2));
	dimension2++;
}

for (int i=1; i<=level; i++){
	for (int j=1; j<=bay; j++){
		table2.cell(i,j).value = 0;
		table3.cell(i,j).value = 22;
	}
}
```

The next section provides a comprehensive description of the Process Flow operations.

4.5 Process Flow

Part of the logic has been integrated into the 3D model as pointed out before, while the logic associated with the vehicles tasks and the SoC calculation for each battery was built in the process flow tool. This is because transportation tasks are more efficient than using the standard 3D operating logic as it can handle customization much better (see FlexSim documentation). The process flow is divided into sections depending on the functions performed. These sections are called containers and are suitable to visualize and keep activities organized. The Process Flow of the model is illustrated in the following figure (Figure 4.11), in which it is possible to see the decision-making logic applied.

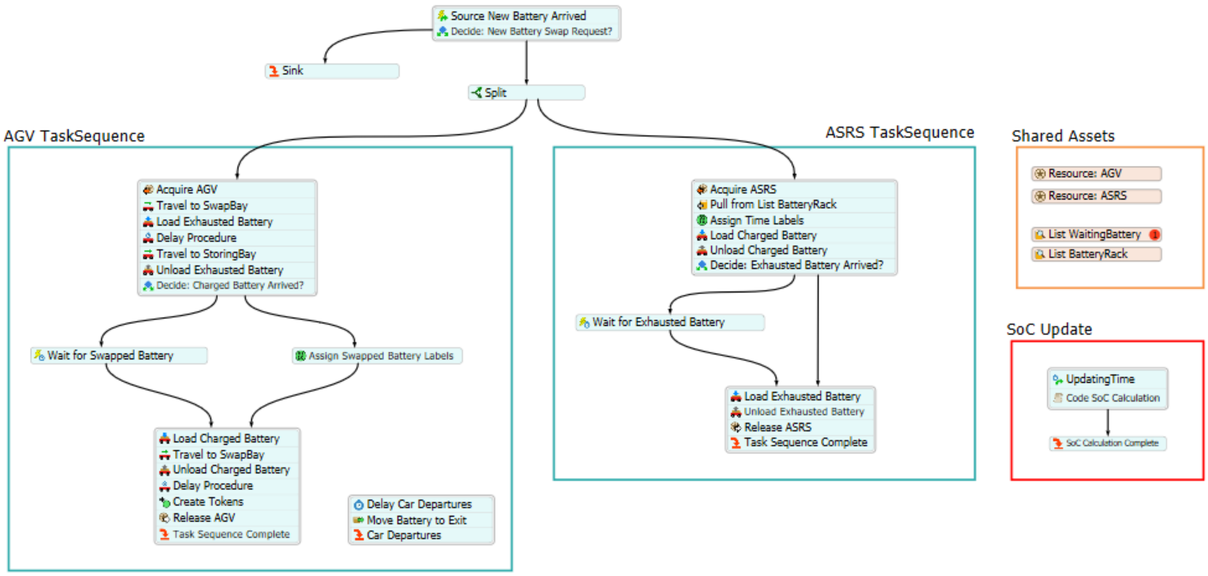


Figure 4.11 The Process Flow of the model developed

- **Shared Assets:** In this container, the Resource blocks as well as the List blocks are found. The resources represent the available task executers, i.e. the AGV and ASRS vehicle. The two lists blocks here are linked to the global lists called *BatteryRack* and *WaitingBattery* that act as a database for every battery in the system. The first list contains all the data about the batteries currently stored inside the warehouse already seen before, such as time of entry, type, capacity, location in the rack, etc. Whenever a battery is retrieved from the rack, it is also removed from the list, and at the same time, each time a battery enters the rack, it is added to the list. While the second list hold the information about the batteries arriving at the station and in *WaitingQueue* currently waiting to be served. The list entries are updated every time a new item joins or leave the *WaitingQueue*.

The event-triggered source *New Battery Arrived* monitors the entry of the *SwapBay* queue and creates a token each time a battery enters it. The token represent the battery swap request and will be associated with that specific battery. The decide activity *New Battery Swap Request* is used to determine whether the battery needs to be replaced or not (i.e. if the battery has already been replaced and is waiting to leave the station). The token is then split in order to acquire simultaneously both the AGV resource and the ASRS resource and in such a way as to manage the operations for the two vehicles in two separate branches. Now the two task executers can begin their task sequences.

- **ASRS TaskSequence:** All the tasks executed by the ASRS are provided in this section. The ASRS performs the retrieval cycle that consist in pulling from the *BatteryRack* list the charged battery that will be swapped with the discharged one and thus inserted in the car. The most charged battery (with the highest SoC) that matches the type of battery required is selected from the list according to the logic discussed in section 4.4. The selection of the battery from the rack has been optimized in such a way as to take first the charged batteries present in the warehouse at the beginning of the simulation and, if these end, among those that have been exchanged and have reached the maximum charge, the one that has longest reached its maximum charge. This minimizes the time a charged battery stays in the warehouse. Moreover, to reduce service times, the puller (ASRS) will take not only the most charged battery but also the one closest to the position in which it is located (i.e. the battery at the shortest distance). See code below for more detail. Once the battery is selected, it is picked up and placed in *RetrievalBay*. After the retrieval cycle is completed, the ASRS performs the storage cycle taking the exhausted battery from the *StoringBay* (if it is present) and inserts it in the warehouse in the same location of the retrieved battery. At the end of this cycle, the battery is pushed to the *BatteryRack* list to store the battery's information and the ASRS resource is released.

```
// Set distance
Variant value = param(1);
Variant puller = param(2);
treenode entry = param(3);
double pushTime = param(4);

if (!objectexists(puller))
      return -1;
treenode ASRS = puller.ASRS;
updatelocations(value);
updatelocations(up(puller));

/**Straight-Line Distance From Resource to Puller*/
double height = getvarnum(ASRS, "forkresetheight");
double x1 = vectorprojectx(value, 0.5 * xsize(value), -0.5 * ysize(value), 0, model());
double y1 = vectorprojecty(value, 0.5 * xsize(value), -0.5 * ysize(value), 0, model());
double z1 = vectorprojectz(value, 0.5 * xsize(value), -0.5 * ysize(value), 0, model());
double x2 = vectorprojectx(ASRS, 0.5 * xsize(ASRS), -0.5 * ysize(ASRS), height, model());
double y2 = vectorprojecty(ASRS, 0.5 * xsize(ASRS), -0.5 * ysize(ASRS), height, model());
double z2 = vectorprojectz(ASRS, 0.5 * xsize(ASRS), -0.5 * ysize(ASRS), height, model());

return sqrt(sqr(x1 - x2) + sqr(y1 - y2) + sqr(z1 - z2));
```

- **AGV TaskSequence:** All the tasks executed by the AGV are provided in this section. Once the AGV resource is acquired, it travels to *SwapBay* to picks up the battery to swap and, after a delay that represents the time it takes the automated mechanism to perform all procedures to remove the empty battery from underneath the car, it transports the battery depositing it in *StoringBay*. At the same time, the AGV picks up the charged battery from the *RetrievalBay* (if it is present) and travels back to *SwapBay* to insert the charged battery into the car (also in this case there is a delay for the automatic procedure). The AGV resource is freed.

A further delay is added (*Delay Car Departures*) and represent the customer that get the car started and leave the station. Finally, the battery is moved to the *OutBattery* sink and it is stored in the global table *BatteryTable* to track valuable information.

- **SoC Update:** In this section, there is the code that constantly updates the SoC of all batteries stored in the rack reading from global table *PowerTable* the power values of chargers. More in detail, the table is used to identify what power value to use based on the item's location in the rack. The *SoC Calculation* code saves the labels values of all batteries in the rack and passes them to the *NewSoC* user command that returns the updated SoC array for all batteries according to the factors and formula seen in Chapter 1 section 1.2. As last step, the *SoC Calculation* code updates the batteries labels and checks if a battery has reached full charge accordingly by changing the *State* and *MaxSoCTime* labels. The *SoC Calculation* code and the *NewSoC* user command are presented below:

```
// SoC calculation
/* Custom Code */
Object obj = model().find("BatteryWarehouse");
Table table = Table("WaitTable");
int dimensionrack = obj.subnodes.length;

Array captot = Array (dimensionrack);
Array charge = Array (dimensionrack);
Array carica = Array (dimensionrack);
Array tempori = Array (dimensionrack);
Array bay = Array (dimensionrack);
Array level = Array (dimensionrack);
double sum = 0;

// Store batteries labels values
for (int i=1; i <= dimensionrack; i++){
       captot [i] = obj.subnodes[i].labels["Capacity"].value;
       charge [i] = obj.subnodes[i].labels["StoringSoC"].value;
       tempori [i] = obj.subnodes[i].labels["EntryTime"].value;
       carica [i] = obj.subnodes[i].labels["SoC"].value;
}

// function that returns the new SoC values based on the power provided by the chargers
Array final = NewSoC(captot, charge, tempori, carica).clone();

// Update all battery SoCs in the warehouse
for (int i=1; i <= dimensionrack; i++){
       obj.subnodes[i].labels.assert("SoC").value = final[i];
       bay [i] = rackgetbayofitem(obj, obj.subnodes[i]);
       level [i] = rackgetlevelofitem(obj, obj.subnodes[i]);

       if (obj.subnodes[i].labels["SoC"].value == MaxLevelRackSoC && tempori[i] != 0 &&
table[level[i]][bay[i]] == 0){
              obj.subnodes[i].labels.assert("State").value = 0;
              obj.subnodes[i].labels.assert("MaxSoCTime").value = time();
              table[level[i]][bay[i]]++;
              }
       sum += obj.subnodes[i].labels.assert("Energy").value;
}
TotEnergy = sum;
```

```
// NewSoC
/* Custom Code*/
// totalcapacity -> param(1);
// storingSoC -> param(2);
// timeofentry -> param(3);
// newSoC -> param(4);

Object obj = model().find("BatteryWarehouse");
int dimensionrack = obj.subnodes.length;

Array age = Array (dimensionrack);
Array per = Array (dimensionrack);
Array tocharge = Array (dimensionrack);
Array bay = Array (dimensionrack);
Array level = Array (dimensionrack);

for (int i=1; i <= dimensionrack; i++){
      if (param(4)[i] < MaxLevelRackSoC){
            age [i] = time() - param(3)[i];
            bay [i] = rackgetbayofitem(obj, obj.subnodes[i]);
            level [i] = rackgetlevelofitem(obj, obj.subnodes[i]);
            per [i] = (param(1)[i] - (age[i]/3600) * Table("PowerTable")
[level[i]][bay[i]])/param(1)[i];
            obj.subnodes[i].labels.assert("Energy").value = Table("PowerTable")
[level[i]][bay[i]]*age[i]/3600;
            tocharge [i] = 1 - per[i];
            param(4)[i] = param(2)[i] + tocharge[i] * 100;
      }
      else
      param(4)[i] = MaxLevelRackSoC;
}
return param(4);
```

4.6 Plan of Experiments

Once the model has been completed and the operation of all the logics has been verified, a series of experiments has been carried out in order to reproduce different operating conditions and scenarios of the BSS with the aim of understanding where it would be more appropriate to invest to improve its performance. These experiments are necessary to understand what the most significant factors are and what their impact on the simulation results is. In particular, the simulations plan will involve the variation of four main elements in the station:

- The number of AGV used
- The number of battery swap workstation (i.e. the *SwapBay* object) used
- The expected state of charge (SoC) percentage of the incoming batteries at the station
- The arrival rate of battery swap requests depending on the number of BSSs

Table 4.2 contains the values of the factors varied in the simulations.

Factor	**Values**
Size of AGV's fleet	1 2 3
No. of Workstations	1 2 3
Expected State of Charge (SoC)[16]	20% 25% 30%
Arrival Rates & No. of BSSs	A B C

Table 4.2 Factor values in simulations

For the arrival rates, the identifiers below have been used:

- A = hourly rates of the average number of EVs that need to recharge the battery considering there are 60 BSSs available in Turin and with an expected SoC of 20, 25 and 30%
- B = hourly rates of the average number of EVs that need to recharge the battery considering there are 65 BSSs available in Turin and with an expected SoC of 20, 25 and 30%
- C = hourly rates of the average number of EVs that need to recharge the battery considering there are 70 BSSs available in Turin and with an expected SoC of 20, 25 and 30%

It is clear that increasing the number of BSSs, decreases the arrival rates at each station.

[16] For each expected SoC value (20%, 25% and 30%), a standard deviation equal to the average has been selected

Table 4.3 reports the three arrival rates (A, B and C) for every expected value of SoC.

	Expected SoC value = 20%			Expected SoC value = 25%			Expected SoC value = 30%		
Time Slots	**No. of EVs**			**No. of EVs**			**No. of EVs**		
00:00 ÷ 01:00	6	5	5	6	6	5	6	6	6
01:00 ÷ 02:00	3	3	2	3	3	3	3	3	3
02:00 ÷ 03:00	2	2	2	2	2	2	2	2	2
03:00 ÷ 04:00	2	2	1	2	2	2	2	2	2
04:00 ÷ 05:00	4	4	3	4	4	4	5	4	4
05:00 ÷ 06:00	8	8	7	9	8	8	10	9	8
06:00 ÷ 07:00	23	21	20	25	23	21	27	25	23
07:00 ÷ 08:00	37	34	32	40	37	34	43	40	37
08:00 ÷ 09:00	35	32	30	38	35	32	41	38	35
09:00 ÷ 10:00	30	27	25	32	29	27	34	32	30
10:00 ÷ 11:00	28	26	24	31	28	26	33	31	28
11:00 ÷ 12:00	28	26	24	30	28	26	33	30	28
12:00 ÷ 13:00	27	25	23	29	27	25	32	29	27
13:00 ÷ 14:00	28	26	24	31	28	26	33	31	28
14:00 ÷ 15:00	30	28	26	32	30	28	35	32	30
15:00 ÷ 16:00	26	24	22	28	26	24	30	28	26
16:00 ÷ 17:00	36	33	31	38	35	33	42	38	36
17:00 ÷ 18:00	38	35	32	41	38	35	44	41	38
18:00 ÷ 19:00	35	32	30	37	34	32	40	37	35
19:00 ÷ 20:00	27	25	23	29	27	25	31	29	27
20:00 ÷ 21:00	17	16	15	19	17	16	20	19	17
21:00 ÷ 22:00	13	12	11	14	13	12	15	14	13
22:00 ÷ 23:00	11	10	10	12	11	10	13	12	11
23:00 ÷ 24:00	10	9	8	10	9	9	11	10	10
Identifier	A	B	C	A	B	C	A	B	C
No. of Stations	60	65	70	60	65	70	60	65	70

Table 4.3 Arrival Rates at different expected SoC values

An example of the scenarios with 3 workstations and an AGV as well as the one with 2 workstations and 2 AGVs are visible in Figure 4.12.

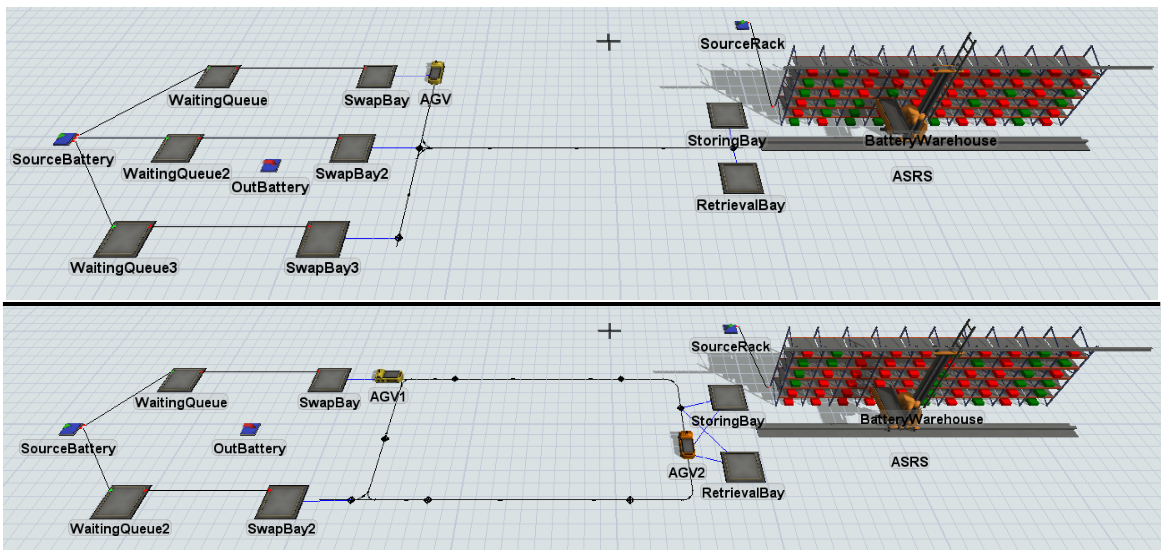


Figure 4.12 Scenarios with 3 workstations, 1 AGV (above) and 2 workstations, 2 AGVs (below)

To manage more AGVs, a network of routes has been created both to avoid collisions between vehicles and to avoid causing deadlocks. Besides this, the logic whereby the AGVs can deal with multiple workstations, not just one has been implemented. Three labels have also been inserted on each AGVs (*Destination*, *Position* and *Busy*) and through the Process Flow it was possible to handle both the movements and the division of tasks between more AGVs.

Moreover, in the case of more than one workstation, in the output flow tab of *SourceBattery* the logic of sending the batteries to the shortest queue has been used, as shown in the code below (suitable for 3 workstations).

```
// Sending logic
Object item = param(1);
Object current = ownerobject(c);
/**Shortest Queue if Available*/
/**Send to the port corresponding to the shortest queue downstream that is available.*/

Object bay1 = model().find("SwapBay");
Object bay2 = model().find("SwapBay2");
Object bay3 = model().find("SwapBay3");
int occupied1 = bay1.labels["Busy"].value;
int occupied2 = bay2.labels["Busy"].value;
int occupied3 = bay3.labels["Busy"].value;

treenode tempobject;
int curmincontent =  1000000000; // this sets the integer to the largest possible value
that an integer can hold
double curminindex = 0;

if ((occupied1 == 1 && occupied2 == 1 && occupied3 == 1) || (occupied1 == 0 && occupied2
== 0 && occupied3 == 0)){
       for (int index = 1; index <= current.outObjects.length; index++) { // numofoutport
              tempobject = current.outObjects[index]; // obj connected to the
outport=index
              if (opavailable(current,index) && tempobject.subnodes.length <
curmincontent) {
                     curmincontent = tempobject.subnodes.length;
                     curminindex = index;
              }
       }
return curminindex; // outputport
}

if (occupied1 == 1 && occupied2 == 0 && occupied3 == 0) // 1,0,0
       return duniform(2,3); // random queue

if (occupied1 == 0 && occupied2 == 1 && occupied3 == 0){ // 0,1,0
       int count = duniform(1,2); // random queue
       if (count == 1){
              return 1;
       }
       if (count == 2){
              return 3;
       }
}
```

```
if (occupied1 == 0 && occupied2 == 0 && occupied3 == 1) // 0,0,1
      return duniform(1,2); // random queue

if (occupied1 == 1 && occupied2 == 1 && occupied3 == 0) // 1,1,0
      return 3;

if (occupied1 == 0 && occupied2 == 1 && occupied3 == 1) // 0,1,1
      return 1;

if (occupied1 == 1 && occupied2 == 0 && occupied3 == 1) // 1,0,1
      return 2;
```

To identify which queue an item belongs to, a label *Queue* is associated that indicates the queue to which it belongs.

The simulations carried out will be aimed at determining the optimal number of stations in Turin. The only limit to the accuracy of the result is the variability of the arrival data. By varying the above-mentioned factors, 81 scenarios are obtained to evaluate the feasibility and the performance of the system. To validate the model, the behavior and functioning of the decisional logics implemented in the software have been tested. Furthermore, to guarantee the repeatability and randomness of results, each experiment is repeated 5 times for 405 simulations as a whole. For the sake of clarity, the first 18 experiments of all the possible 81 scenarios are listed in Table 4.4.

No. of Experiment	No. of AGVs	No. of Workstations	Average State Of Charge (SoC)	Arrival Rates
1 2 3	1	1	20%	A B C
4 5 6	1	1	25%	A B C
7 8 9	1	1	30%	A B C
10 11 12	2	1	20%	A B C
13 14 15	2	1	25%	A B C
16 17 18	2	1	30%	A B C

Table 4.4 First 18 experiments out of 81 conducted

The others parameter values used in the simulations and explained in section 4.4 are shown in Table 4.5.

	Value
MaxLevelRackSoC	90
UpdatingTime	0.10
DelayTime	10
DepartureTime	10

Table 4.5 Simulation Parameters

Through FlexSim Experimenter tool, it has been possible to run the simulation model several times, changing more than one parameters to obtain a set of scenarios with statistical data about different results. Figure 4.13 displays the Experimenter tool. Each simulation launched ends once it reaches 24 hours of activity.

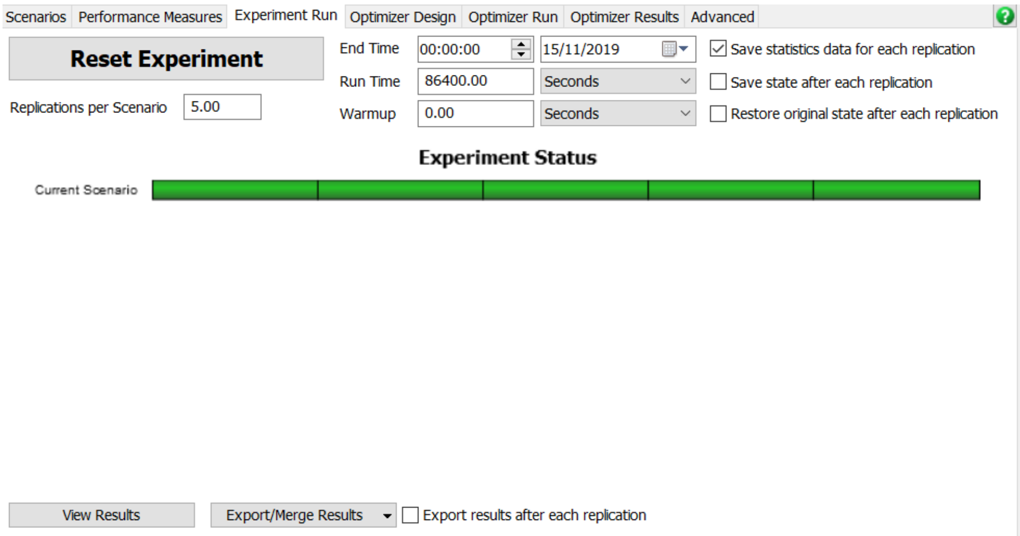


Figure 4.13 FlexSim's Experimenter tool

4.7 Collection Methodology of Results

Through the study and evaluation of the characteristics of the system (with the analysis of performance), the optimal values of the parameters of interest are defined and the critical points (bottlenecks) of the built model are determined.

The parameters and performance measures observed, that have been tracked and collected from each simulation experiment, are related to:

- Average value and standard deviation for Customer Waiting Time
- Average value and standard deviation for Service Time
- Average value and standard deviation for Battery Charge Level Provided
- Daily energy required by the station
- Average value and standard deviation for Staytime of fully charged batteries in the rack
- Average value and standard deviation for Charging time
- Average Vehicles (AGV and ASRS) Utilization

Moreover, both the number of batteries delivered not at full charge and the number of recharged batteries are stored. Figure 4.14 shows the key performance indicators (KPIs) measured in each scenario.

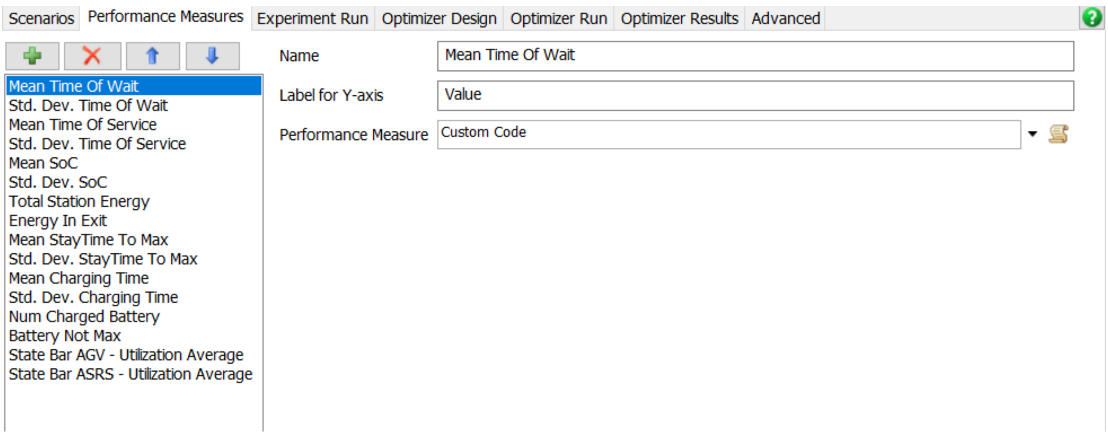


Figure 4.14 KPIs measured through the Experimenter tool

The data collection has been carried out by storing a series of significant moments of time, in which a certain action takes place. In practice, time information of the various activities are directly stored in the items' labels. All items' information will be accessible in the form of global table at the end of the simulation. Table 4.6 shows the global table *BatteryTable* that contains data about batteries leaving the station, among which are:

- *Type:* the battery type;
- *Capacity*: the battery capacity (in kWh);
- *StoringSoC*: the battery charge level when it entered the warehouse (in %);

- *SoC*: the battery charge level when it left the warehouse (in %);
- *EntryTime*: the time when the battery enters the warehouse (in sec);
- *MaxSoCTime*: the time when the battery reaches its maximum charge (in sec);
- *OutTime*: the time when the battery leaves the warehouse (in sec);
- *State*: the battery status;
- *Energy*: the energy used to recharge the battery (in kWh);
- *StayTimeToMax*: the dwell time of fully charged battery in the warehouse, in other words is the difference between *OutTime* and *MaxSoCTime* (in sec);
- *ChargingTime*: the time when the battery has been in charge in the warehouse, that is to say the difference between *OutTime* and *EntryTime* for the batteries that have not reached their maximum charge and between *MaxSoCTime* and *EntryTime* for the batteries that have reached the maximum charge (in sec)

	Type	Capacity	StoringSoC	SoC	EntryTime	MaxSoCTime	OutTime	State	Energy	StayTime	StayTimeToMax	ChargingTime
Battery 57	2	75	90	90	0	0	6106.50	-1	0	6106.50	6106.50	0
Battery 58	1	41	90	90	0	0	6216.84	-1	0	6216.84	6216.84	0
Battery 59	1	41	90	90	0	0	6320.82	-1	0	6320.82	6320.82	0
Battery 60	2	75	90	90	0	0	6436.77	-1	0	6436.77	6436.77	0
Battery 61	1	41	27.19	90	142.58	4356.60	6552.06	0	25.75	6409.48	2195.46	4214.02
Battery 62	1	41	27.25	90	783.41	4993.60	6662.61	0	25.73	5879.20	1669.01	4210.19
Battery 63	2	75	41.73	73.59	2863.91	-1	6774.60	1	23.90	3910.69	0	3910.69
Battery 64	2	75	25.09	73.00	1002.34	-1	6881.89	1	35.93	5879.55	0	5879.55
Battery 65	1	41	18.24	90	360.90	5175.50	6997.18	0	29.42	6636.28	1821.68	4814.60
Battery 66	1	41	37.68	90	1677.91	5188.20	7103.16	0	21.45	5425.26	1914.96	3510.29
Battery 67	1	41	12.92	90	254.48	5425.80	7216.45	0	31.60	6961.97	1790.65	5171.32
Battery 68	2	75	11.97	67.00	566.38	-1	7319.85	1	41.27	6753.46	0	6753.46
Battery 69	1	41	14.98	90	457.86	5491.10	7425.14	0	30.76	6967.28	1934.04	5033.24
Battery 70	1	41	20.62	90	891.05	5546.10	7532.53	0	28.45	6641.48	1986.43	4655.05

Table 4.6 Stored Data for Batteries in BatteryTable

It is important to underline that, since there is the possibility to provide the customer with batteries that have not reached the maximum charge (i.e. where the *State* attribute is equal to 1), these batteries will have negative values for *MaxSoCTime* label and zero value for *StayTimeToMax* label.

In an additional table (Table 4.7), called *CustomersTable*, it is possible to read meaningful details for the customers at the station like:

- *StartWait:* the time when the customer starts waiting for his turn (in sec);
- *EndWait:* the time when the customer's turn has come (in sec);
- *StartService:* the time when the customer starts to be served (in sec);
- *EndService*: the time when the customer was served (in sec);

- *TimeOfWait*: the time elapsed from when the customer enters the station to when he is served, which is the difference between *EndWait* and *StartWait* (in sec);
- *TimeOfService*: the actual customer service time, that is the difference between *EndService* and *StartService* (in sec)

	StartWait	EndWait	StartService	EndService	TimeOfWait	TimeOfService	TimeInStation
Customer 57	5700	6132.62	6132.62	6222.96	432.62	90.33	522.96
Customer 58	5800	6242.96	6242.96	6331.29	442.96	88.33	531.29
Customer 59	5900	6351.29	6351.29	6442.89	451.29	91.60	542.89
Customer 60	6000	6462.89	6462.89	6559.22	462.89	96.33	559.22
Customer 61	6100	6579.22	6579.22	6669.77	479.22	90.55	569.77
Customer 62	6200	6689.77	6689.77	6785.06	489.77	95.29	585.06
Customer 63	6300	6805.06	6805.06	6897.05	505.06	91.99	597.05
Customer 64	6400	6917.05	6917.05	7006.34	517.05	89.29	606.34
Customer 65	6500	7026.34	7026.34	7113.63	526.34	87.29	613.63
Customer 66	6600	7133.63	7133.63	7225.61	533.63	91.99	625.61
Customer 67	6700	7245.61	7245.61	7331.01	545.61	85.39	631.01
Customer 68	6800	7351.01	7351.01	7440.30	551.01	89.29	640.30
Customer 69	6900	7460.30	7460.30	7545.69	560.30	85.39	645.69
Customer 70	7000	7565.69	7565.69	7654.98	565.69	89.29	654.98

Table 4.7 Stored Data for Customers in CustomersTable

With reference to the total energy required by the station, this is stored at the end of each simulation in the global variable *StationEnergy* which is equivalent to the sum of the energy used to recharge the batteries in the warehouse at the end of the simulation (*TotEnergy*) and that used for the replaced batteries that left the station (*AddEnergy*).

After running the Experimenter for each scenario, to see all performance measures for all replications, a SQL query is entered in a calculated table as shown in the image below (Figure 4.15):

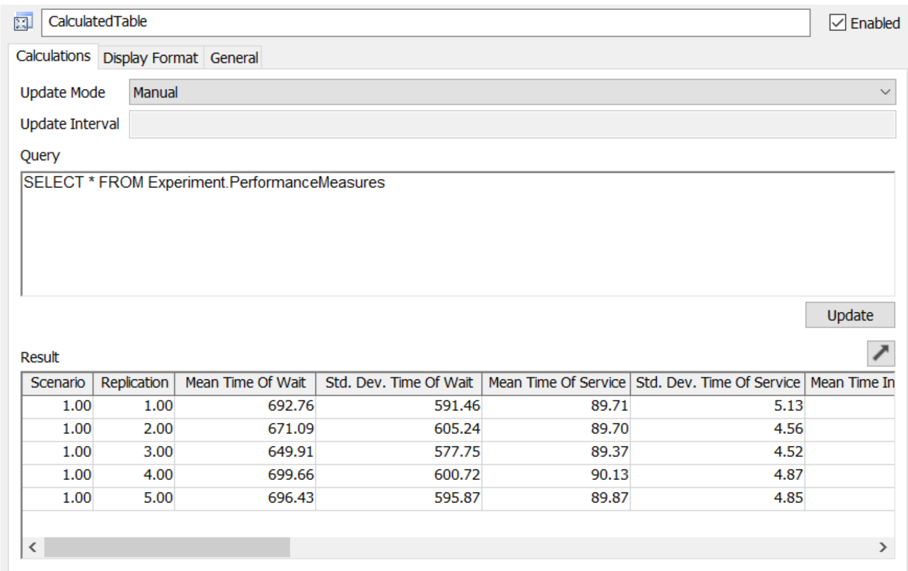


Figure 4.15 Example of calculated table's result

From here, data can be exported in table as comma-separated values (CSV) format, where they will be analyzed in an Excel spreadsheet to create charts like boxplots and to calculate useful statistics.
For each experiment carried out, a descriptive analysis of the data will be presented to observe the distribution and qualitatively identify the factors that most affect the performance of the system. The results of the 5 replications for each experiment of the model described above are reported in the next chapter.

5 Results and Discussion

Before testing the various experiments, it was necessary to determine which scenarios were meaningful to be investigated. After a preliminary observation on the responsiveness of the model, it was noticed that in the scenarios in which the number of AGVs is greater than the number of workstations, the percentage of vehicles utilization was very low and therefore they have not been studied. For this reason, it was decided to consider only the cases in which the number of vehicles (AGVs) is less than or equal to the number of battery swap workstation, which means considering the remaining 54 scenarios after deleting the scenarios corresponding to the configurations to be discarded.
Figure 5.1 illustrates the updated experimental plan without the scenarios that were thrown away.
Comparisons on the incidence of the main factors on station performance will now follow. To simplify the reading of the graphs below, the simulations results will be grouped by expected SoC value (20%, 25% and 30%). The graphs underneath show be the KPIs discussed and analyzed in Chapter 4 section 4.7 (vertical y-axis) depending the configurations subdivided by number of stations, number of workstations and number of AGVs (horizontal x-axis).

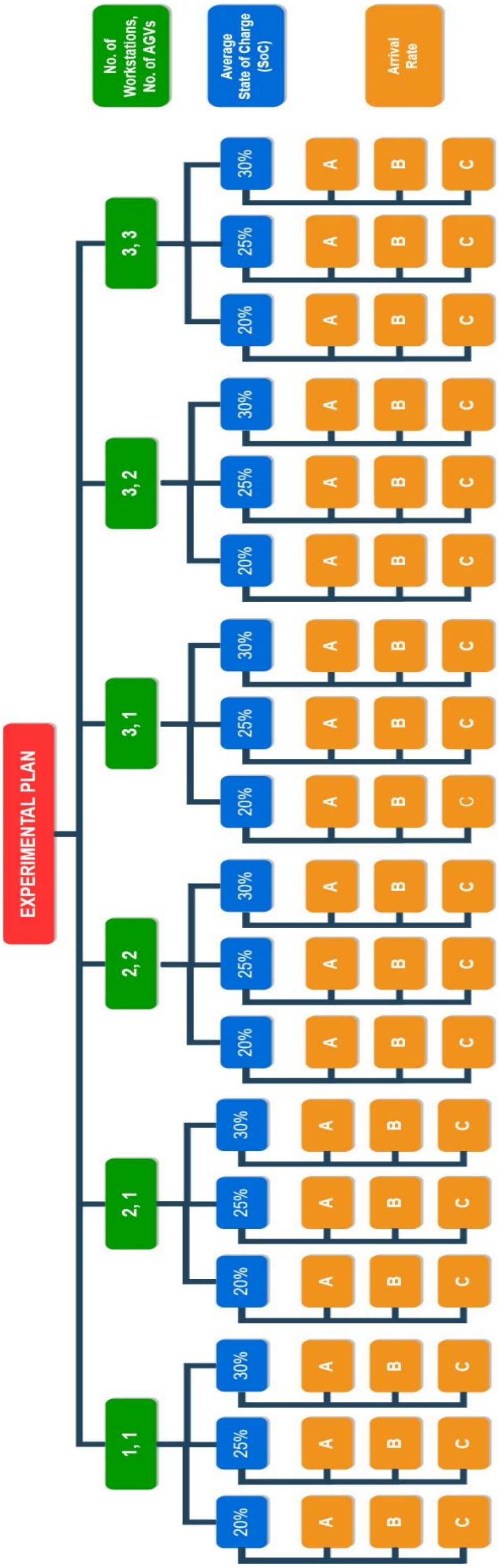


Figure 5.1 Updated Experimental Plan

5.1 Waiting & Service Time

The waiting time is clearly one of the most interesting factors to evaluate. Dividing the results obtained according to the number of stations together with the number of workstations and AGVs, a separation of performance is obtained.
With the same number of stations, the customers' waiting time is shortened and so there is a considerable time saving if the number of workstations used is equal to the number of AGVs, while it increases if the workstations are greater than the AGVs (see Figures 5.2, 5.3 and 5.4). Same considerations holds for service time but it can be observed that using 3 workstations and 3 AGVs compared to 2 workstations and 2 AGVs there are slightly worse service times as the number of arrivals at the station increases (that is when the number of stations used decreases): this is due to the ASRS which represents the bottleneck for these systems (see Figures 5.5, 5.6 and 5.7).

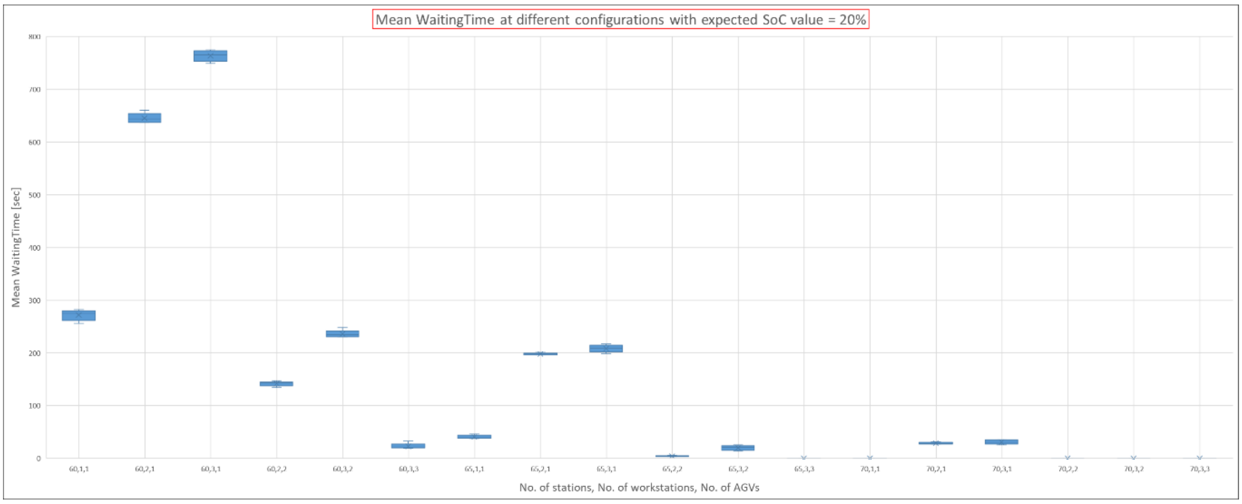


Figure 5.2 Mean WaitingTime for Expected SoC value = 20 %

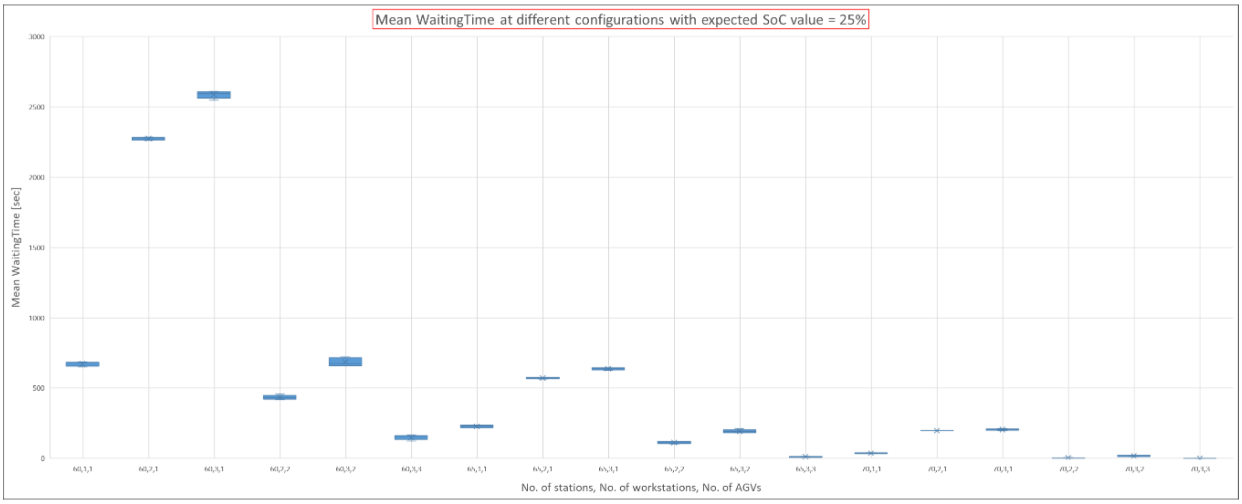


Figure 5.3 Mean WaitingTime for Expected SoC value = 25%

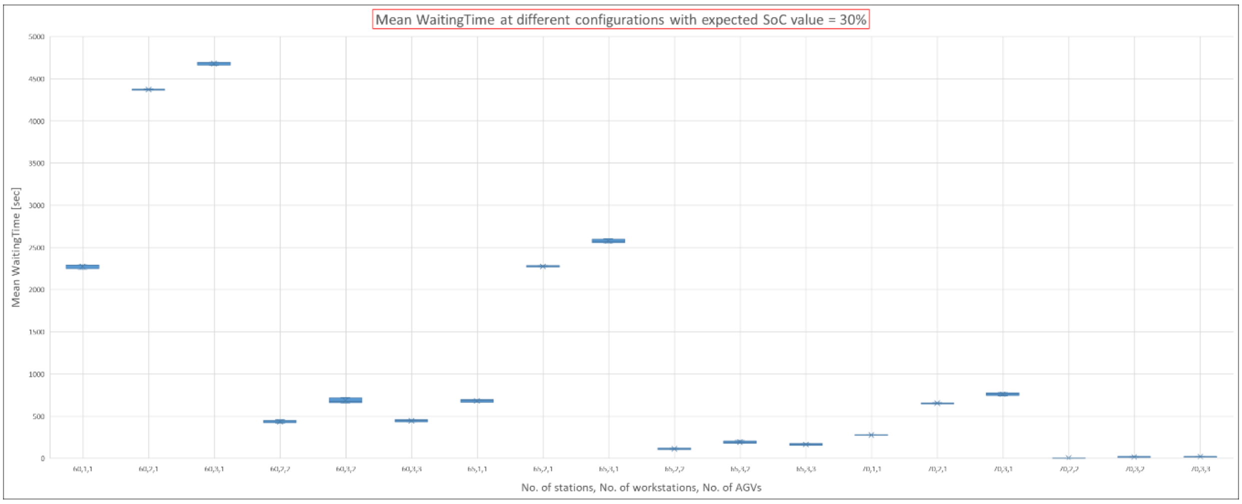


Figure 5.4 Mean WaitingTime for Expected SoC value = 30%

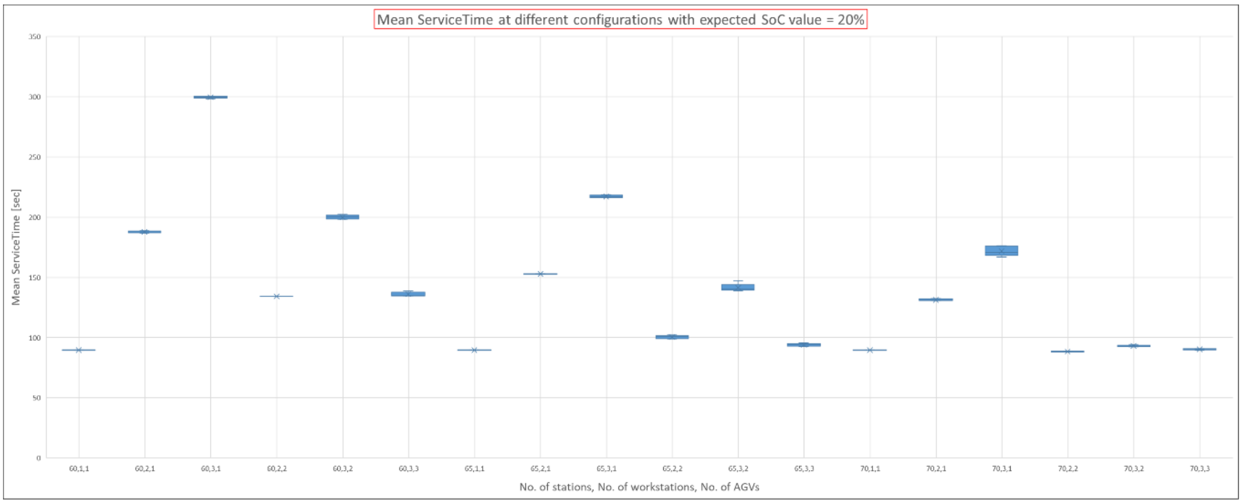


Figure 5.5 Mean ServiceTime for Expected SoC value = 20%

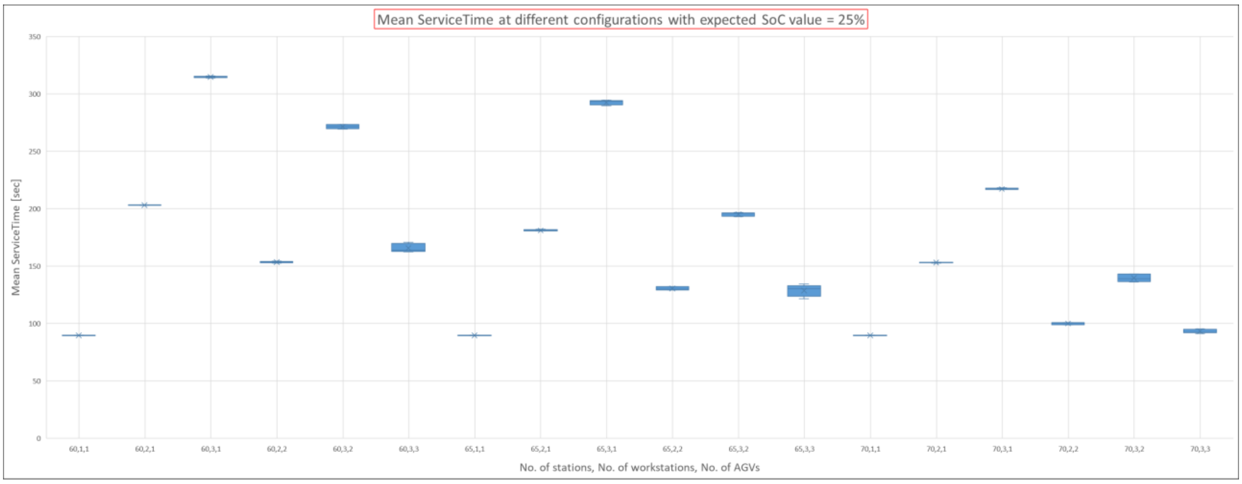


Figure 5.6 Mean ServiceTime for Expected SoC value = 25%

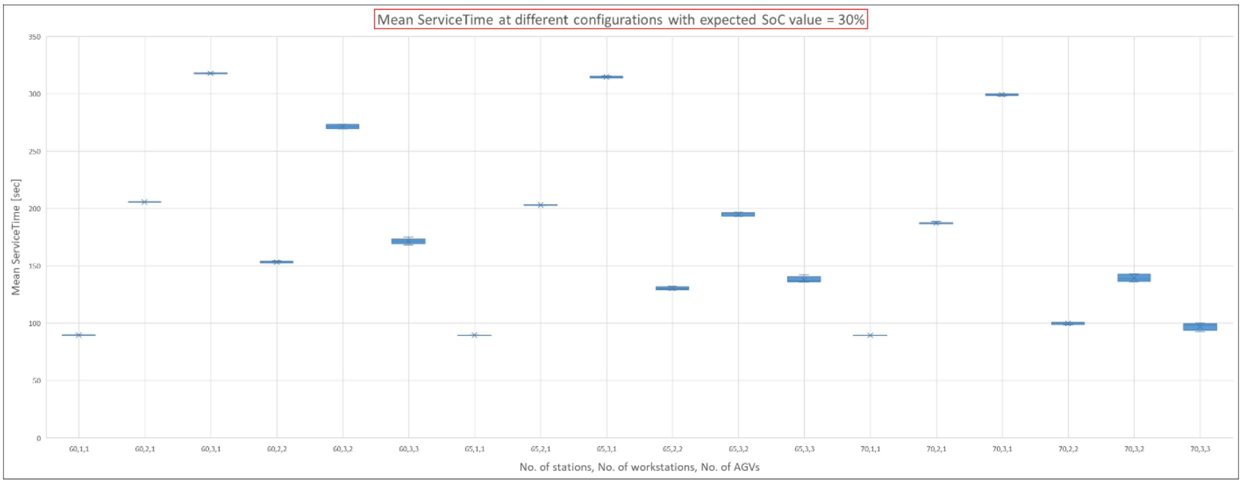


Figure 5.7 Mean ServiceTime for Expected SoC value = 30%

5.2 SoC of the provided batteries

As regards the percentage of charge of the batteries provided to customers, it can be noted how, increasing the number of stations (from 60 to 70), the number of cars arriving at each station decreases and therefore the percentage of the battery charge level (SoC) increases (see Figures 5.8, 5.9 and 5.10). This is because the batteries in the warehouse have more time to recharge. It is worth noting that the SoC values are barely below the maximum charge level chosen that is 90% (dashed red line).

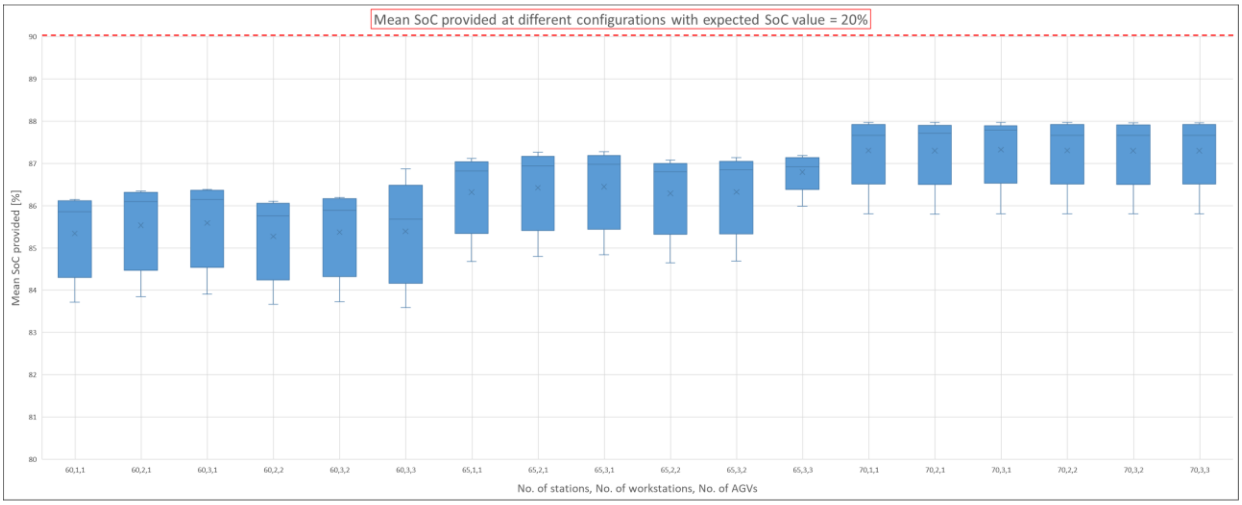


Figure 5.8 Mean SoC provided for Expected SoC value = 20%

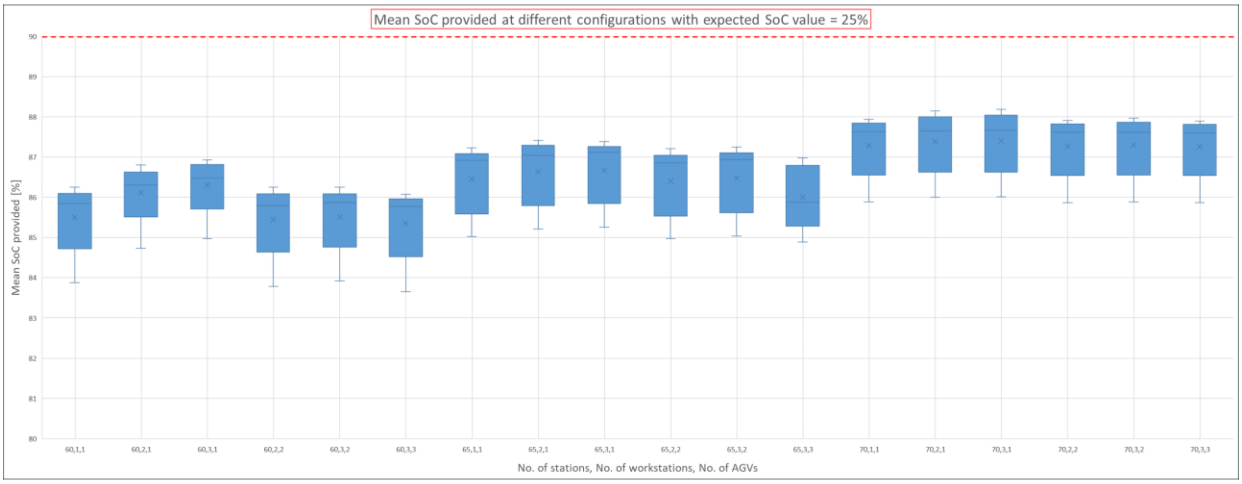


Figure 5.9 Mean SoC provided for Expected SoC value = 25%

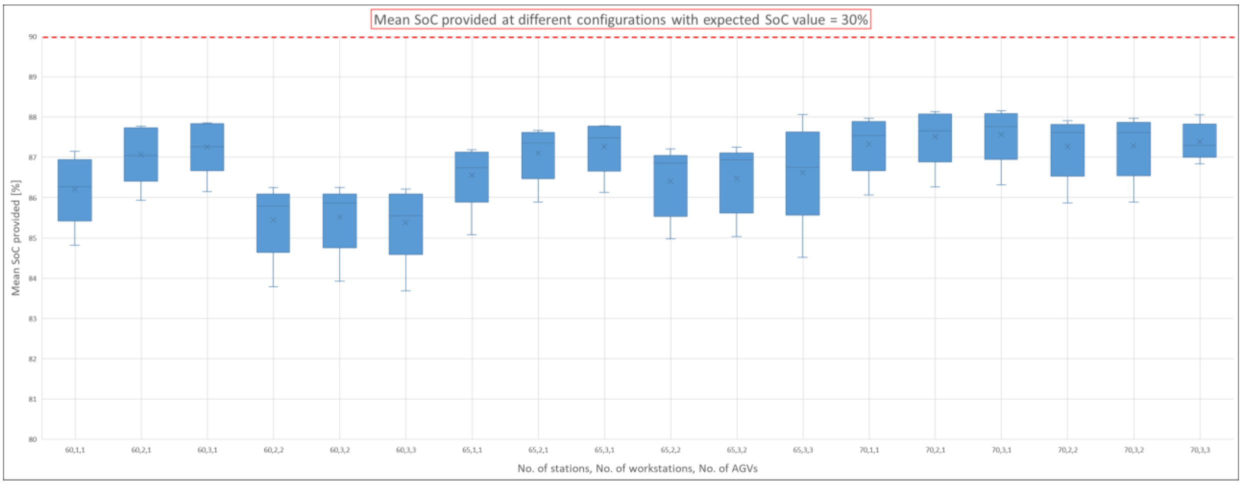


Figure 5.10 Mean SoC provided for Expected SoC value = 30%

5.3 Energy consumption by the station

A contrary trend to the previous one can be observed for the energy absorbed by the station to charge the batteries in the warehouse. In particular, as the number of arrivals at the stations decreases, the less batteries to recharge there will be and so less energy required by the stations (see Figures 5.11, 5.12 and 5.13).

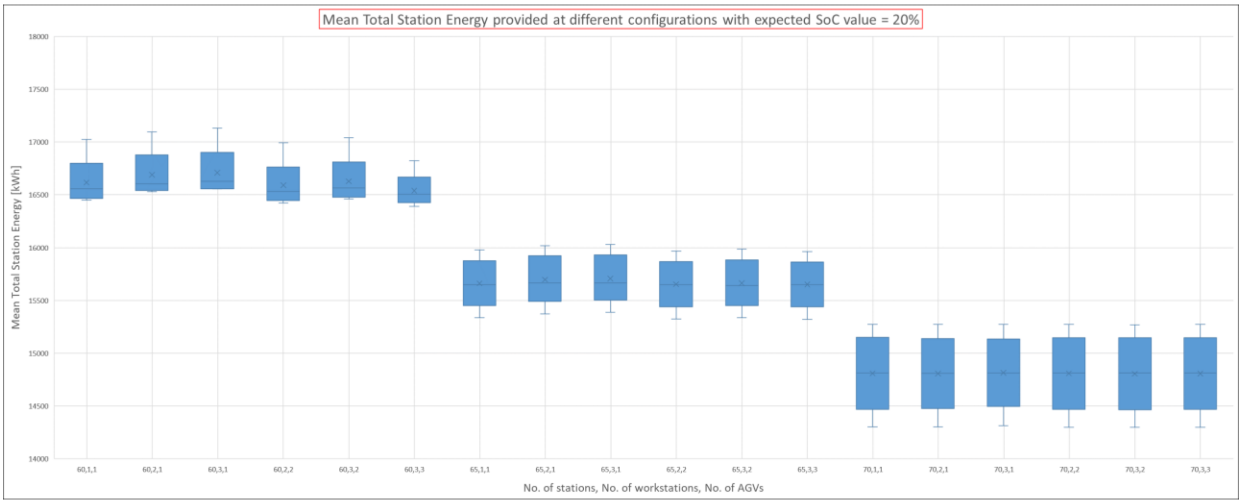


Figure 5.11 Mean Total Station Energy for Expected SoC value = 20%

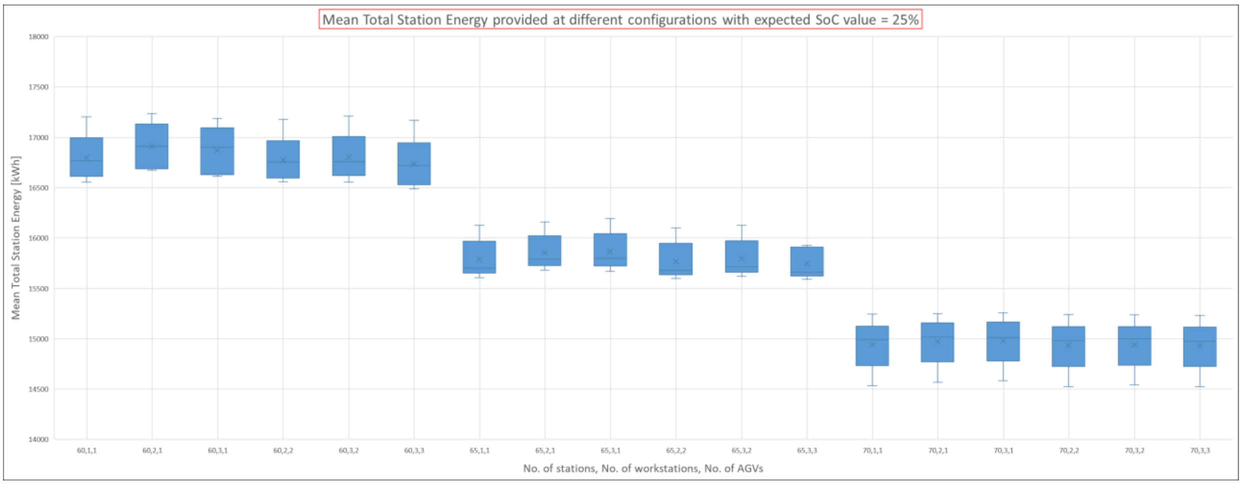


Figure 5.12 Mean Total Station Energy for Expected SoC value = 25%

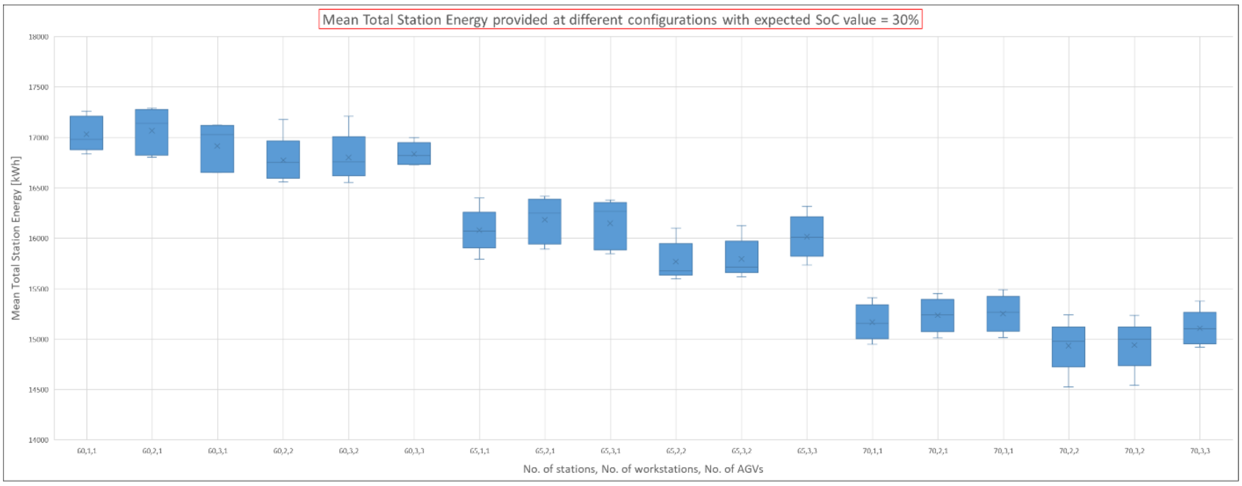


Figure 5.13 Mean Total Station Energy for Expected SoC value = 30%

5.4 Staytime from maximum charge level of batteries in the rack

In this case, it can be easily verified from the results that, as the number of stations used increases, the fully charged batteries remain in the warehouse for longer, consequence of the fact that they stay in charge longer (see section below). The boxplots also indicates the percentages of batteries supplied to the customer that have not reached the maximum charge (SoC = 90%). This percentage is decreased as the number of stations employed increases (see Figures 5.14, 5.15 and 5.16).

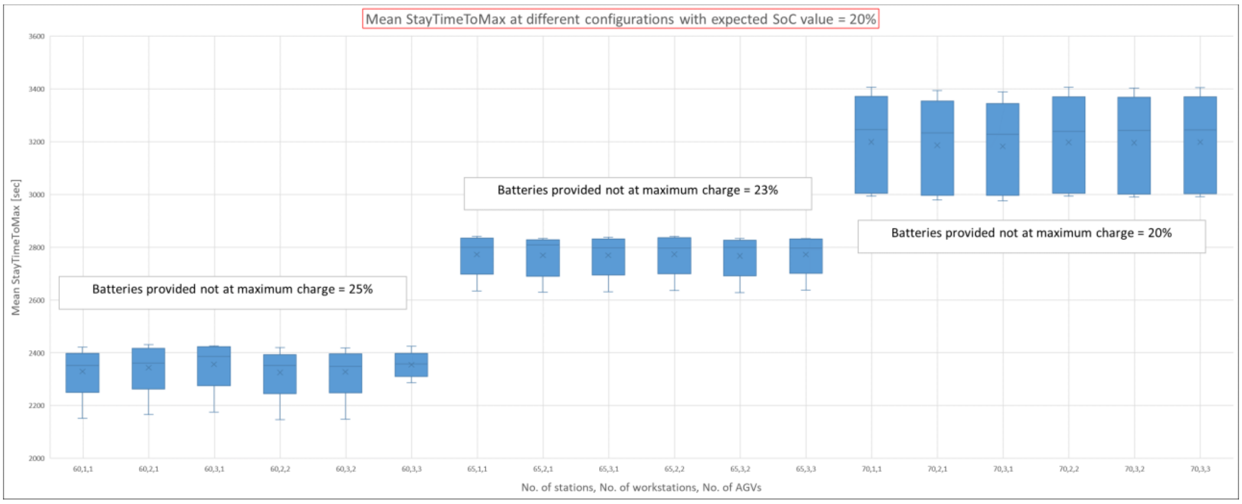


Figure 5.14 Mean StayTimeToMax for Expected SoC value = 20%

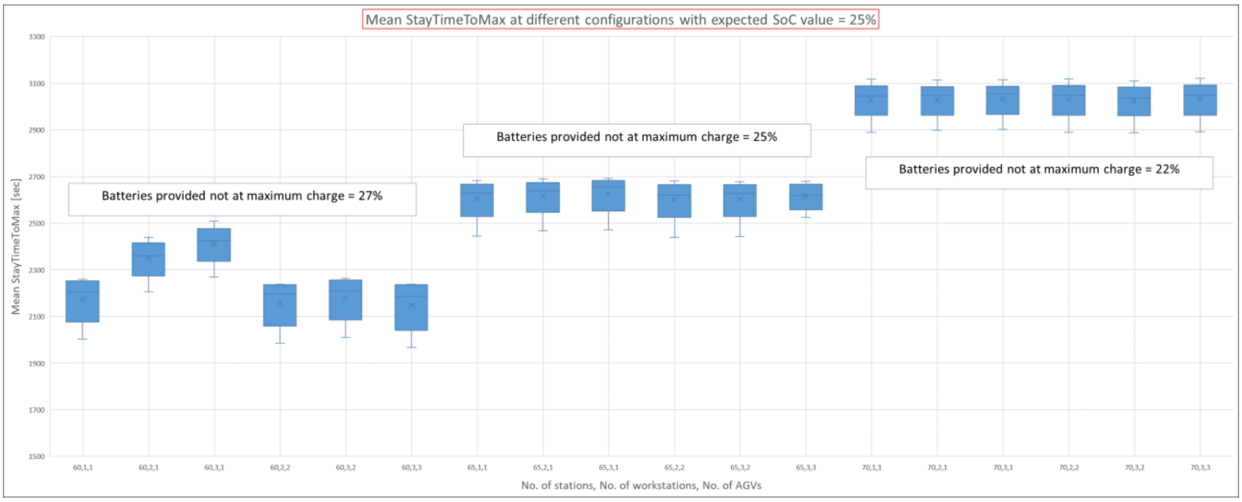


Figure 5.15 Mean StayTimeToMax for Expected SoC value = 25%

Figure 5.16 Mean StayTimeToMax for Expected SoC value = 30%

5.5 Charging Time

Classifying the results according to the time that the batteries remain in charge in the warehouse, the following situation is obtained, in which the dashed red line indicates the average weighted charging time from the expected SoC value (20, 25 or 30%) to the maximum charge (90%). It is interesting to observe that the results are slightly below this average but still of the order of minutes, which means that the batteries supplied will be slightly below the maximum charge (see Figures 5.17, 5.18 and 5.19). Again, by increasing the number of stations and thus decreasing the number of cars arriving at each station, the batteries in the warehouse have more time to recharge. This is a direct consequence of the performances already observed for the average percentage of charge of the batteries provided to customers (see section 5.2).

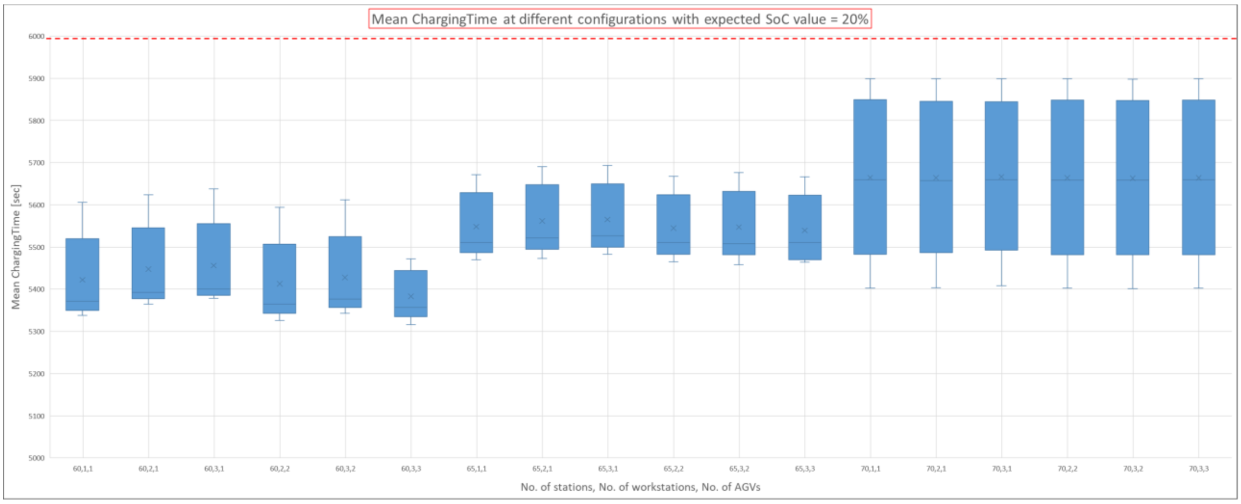


Figure 5.17 Mean ChargingTime for Expected SoC value = 20%

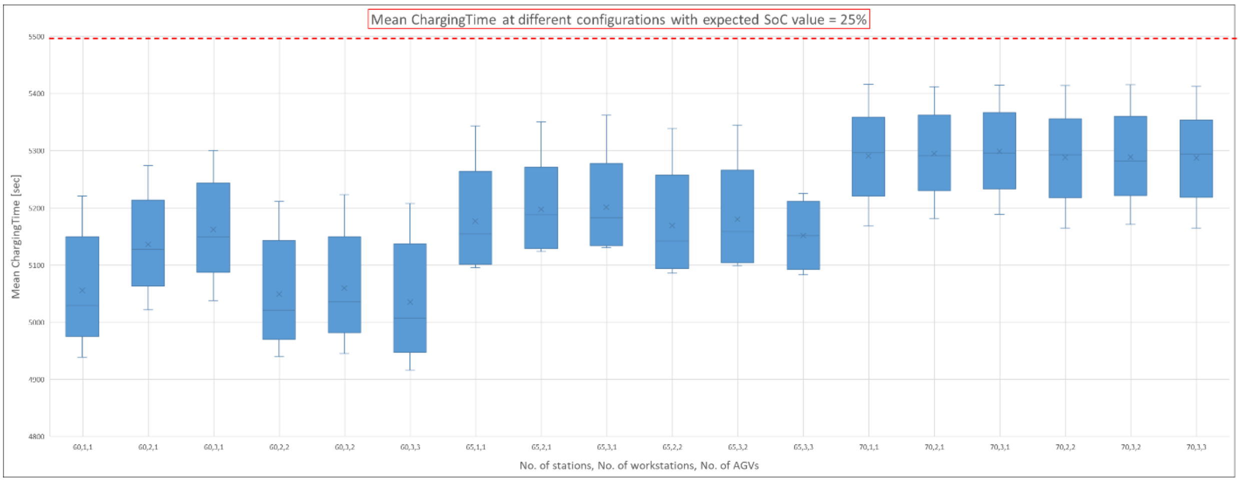


Figure 5.18 Mean ChargingTime for Expected SoC value = 25%

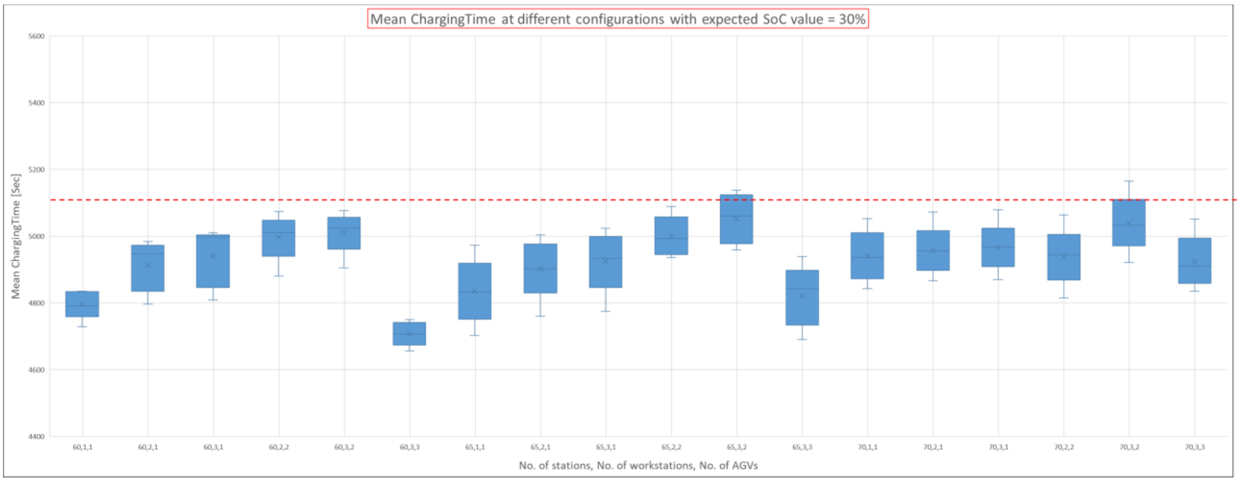


Figure 5.19 Mean ChargingTime for Expected SoC value = 30%

5.6 Vehicles Utilization

It is also noteworthy the average vehicle utilization indicator for both AGVs and ASRS (see Figures 5.20, 5.21, 5.22 and 5.23, 5.24, 5.25). Especially for the AGVs, the utilization percentages are high when the latter are in lower number than the number of workstations, while there are in general low utilization percentages when fewer arrivals are registered, i.e. when using a growing number of stations. As far as the ASRS is concerned, there is a progressive decrease in the utilization percentage as the number of stations increases.

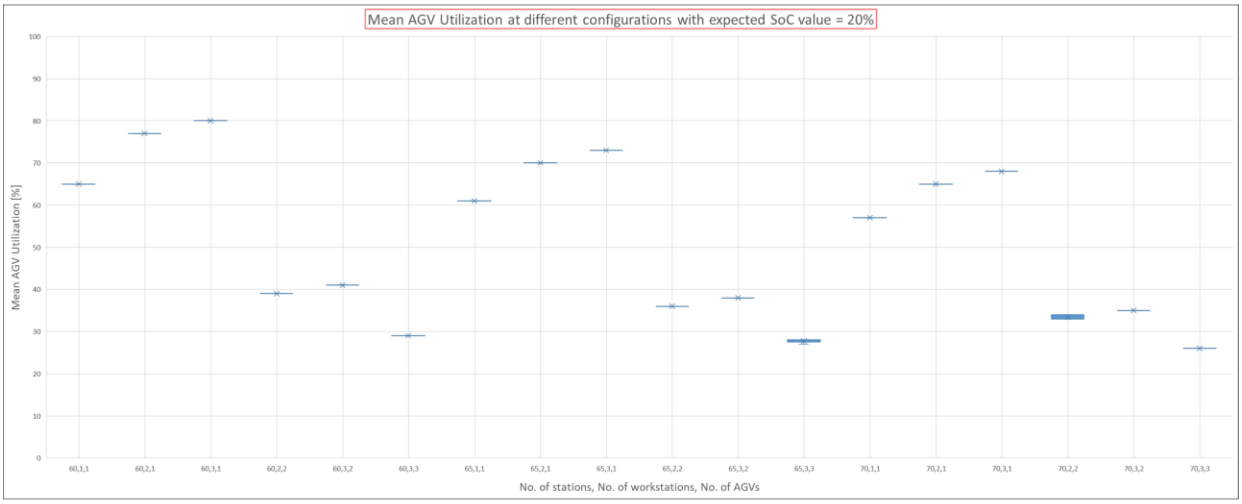


Figure 5.20 Mean AGV Utilization for Expected SoC value = 20%

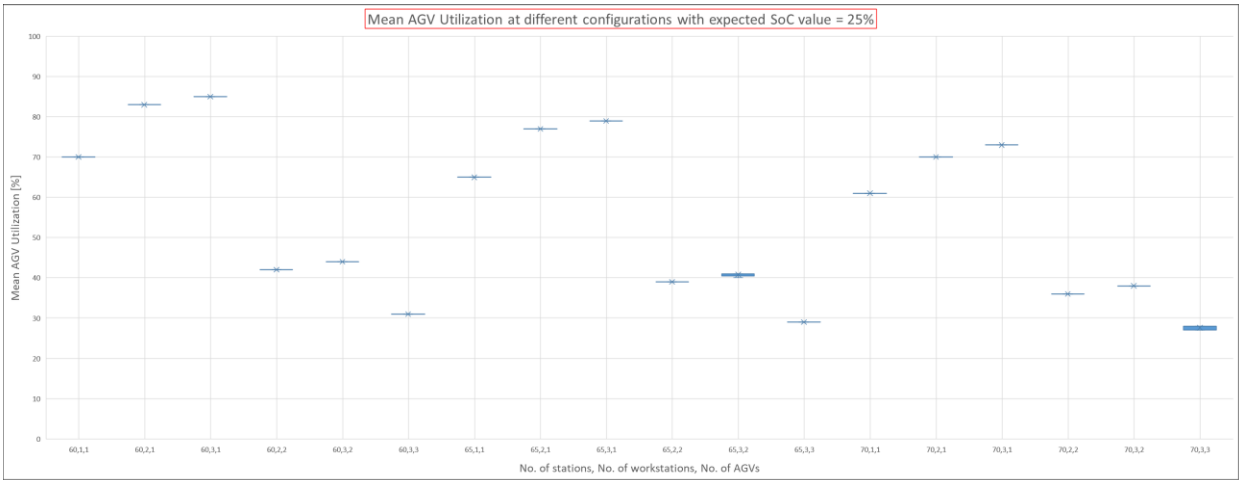


Figure 5.21 Mean AGV Utilization for Expected SoC value = 25%

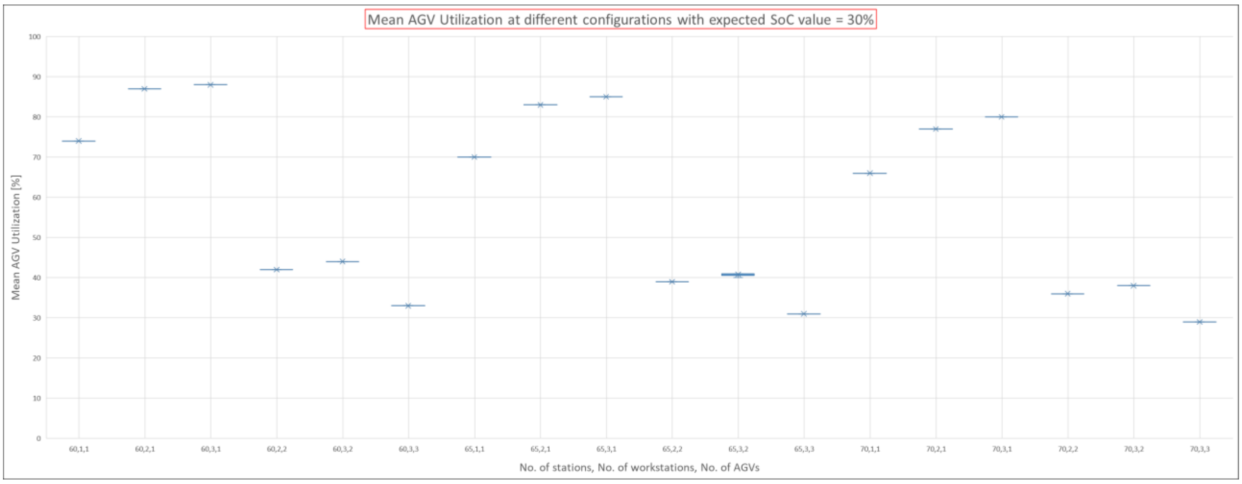


Figure 5.22 Mean AGV Utilization for Expected SoC value = 30%

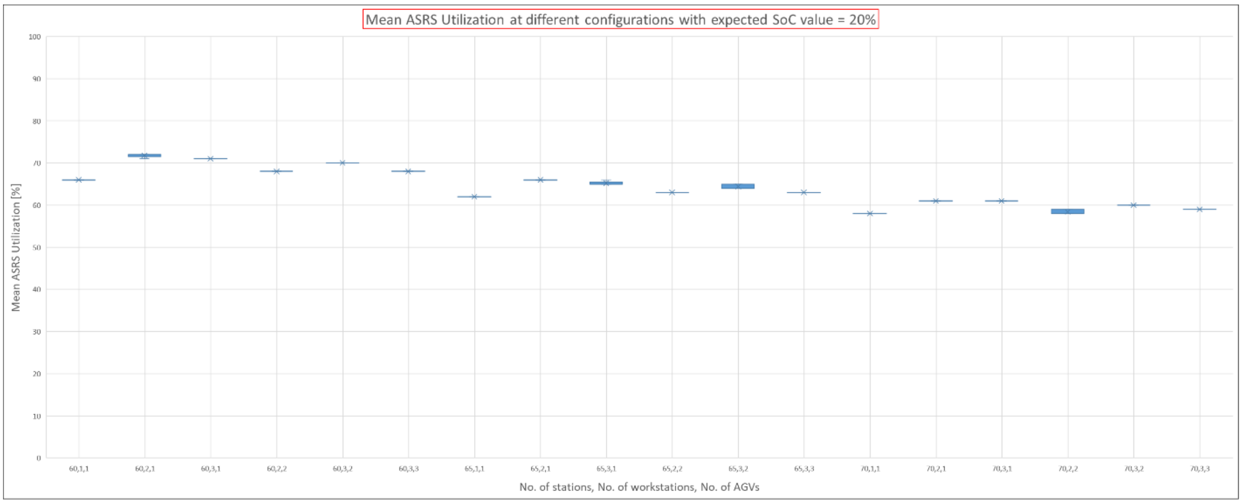


Figure 5.23 Mean ASRS Utilization for Expected SoC value = 20%

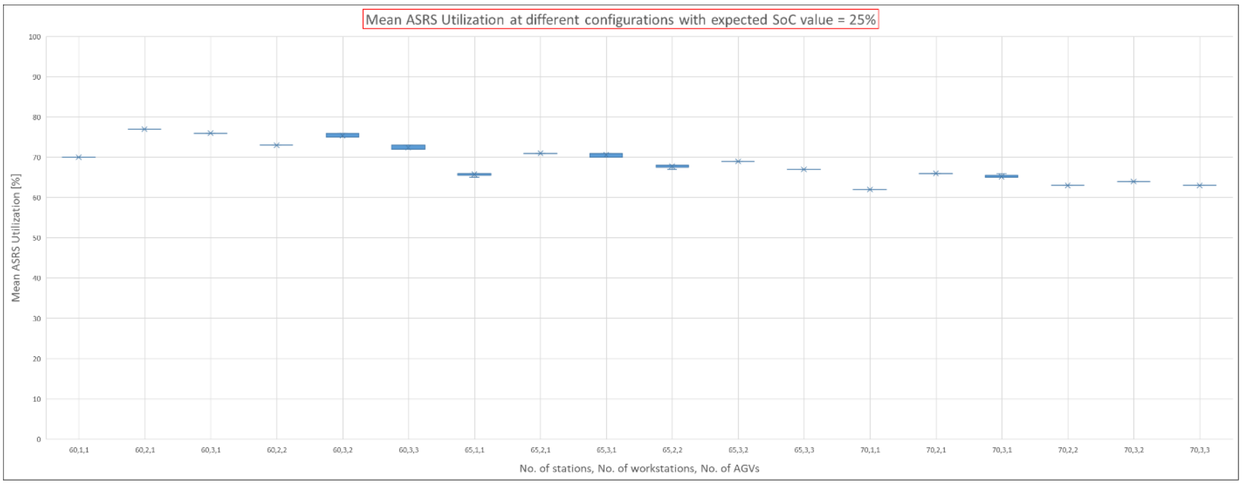


Figure 5.24 Mean ASRS Utilization for Expected SoC value = 25%

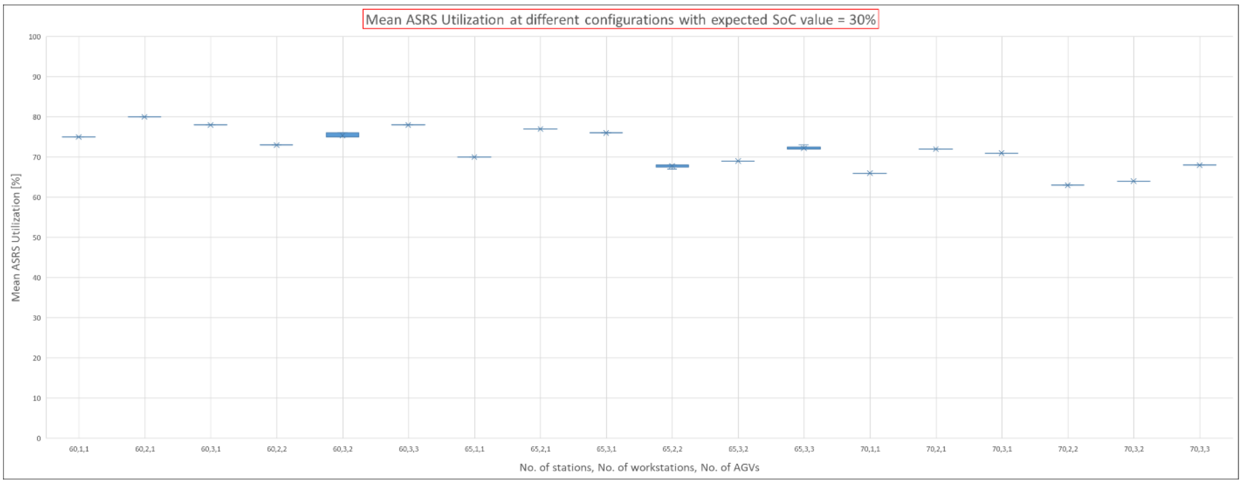


Figure 5.25 Mean ASRS Utilization for Expected SoC value = 30%

To understand the importance of these outcomes and to compare the performances obtained between the simulations carried out, a more in-depth analysis follows.

5.7 Optimal configuration for expected SoC value

The purpose of this thesis is to choose the configuration that best fits the urban area of Turin minimizing or maximizing at the same time some selected criteria.
In order to evaluate which of all the possible alternatives is the best solution, a Multiple-Criteria Decision Analysis (MCDA) approach is used because it is capable of simultaneously taking into account and comparing a set of alternatives according to their suitability.
The MCDA is a discipline in the category of operational research, oriented to support the decision-maker whenever he has to operate with numerous and conflicting evaluations.
Among the most frequently used multi-criteria decision-making methods (Figure 5.26), the one called "Technique for Order Preference by Similarity to Ideal Solution" (*TOPSIS*) has been applied since it is more suitable for this study case with a large number of criteria and alternatives. This technique was developed by Ching-Lai Hwang and Yoon in 1981 [36]. Essentially, it is based on the choice of the best alternative through the similarity with the ideal solution.
More specifically, this method classifies the alternatives in such a way that the best alternative should be the one that is closest to the positive ideal solution (i.e. the one composed of all best values reachable) and farthest from the negative ideal solution (i.e. the one that consists of all the worst values achievable).

- Multi-Attribute Utility Theory (MAUT)
- Analytic Hierarchy Process (AHP)
- Fuzzy Set Theory
- Analytic Network Process (ANP)
- Case-based Reasoning
- Data Envelopment Analysis
- Simple Multi-Attribute Rating Technique
- Goal Programming
- **ELECTRE**
- PROMETHEE
- **Weighted Averaged Sum (WAS)**
- Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)
- Additive Ratio ASsessment (ARAS).

Figure 5.26 Multi Criteria Decision Analysis Methods [37]

The main steps involved in this multi-criteria decision making technique are the following [38] and are illustrated in Figure 5.27:

1. Construct the decision matrix and determine the weight of the criteria
2. Compute the normalized decision matrix
3. Compute the weighted normalized decision matrix
4. Define the positive and negative ideal solutions
5. Compute the separation measures from the positive ideal solution and the negative ideal solution
6. Compute the relative nearness to the positive ideal solution
7. Rank the preference order and select the alternative closest to 1

This section is focused on the application of the *TOPSIS* method to the case considered.

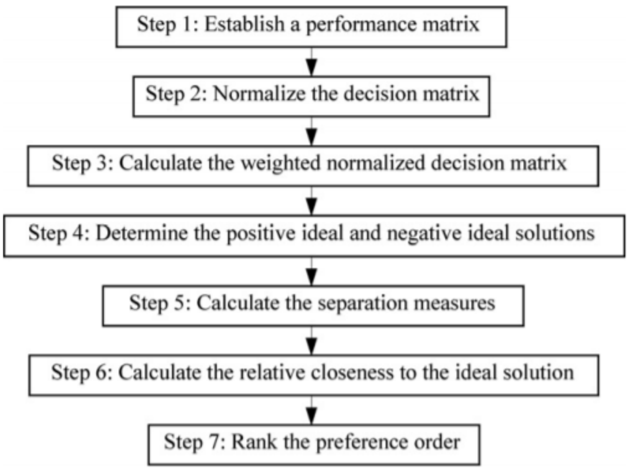


Figure 5.27 TOPSIS method algorithm [39]

In this case, the alternatives are 18 and are characterized by the number of BSS, workstations and AGVs (see Figure 5.28). While the criteria chosen are 14 and are referred to the cost of infrastructure and energy employed, the quality of service (waiting time, service time and % of SoC provided) and, lastly, the battery preservation (battery staytime and charging time). In Figure 5.29, it is possible to see the hierarchical tree with (aggregate) weights assigned to the various criteria and also the criteria to be maximized (in green) and minimized (in red).

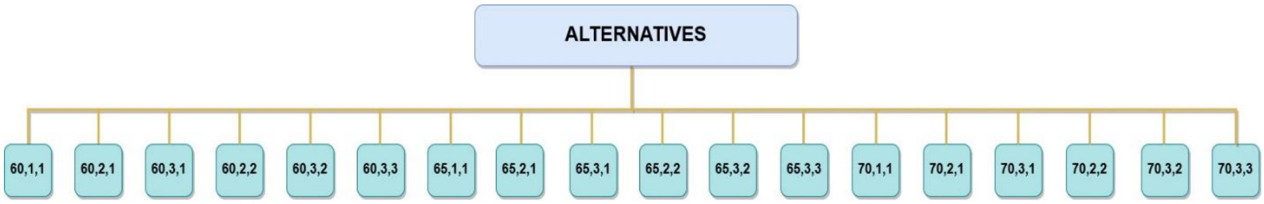


Figure 5.28 All the 18 alternatives examined

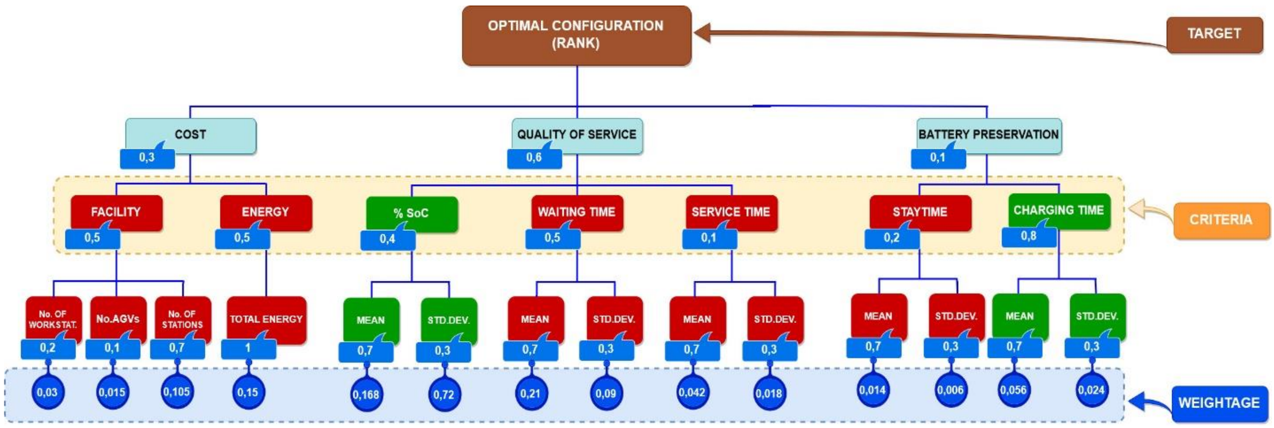


Figure 5.29 Weights tree assigned to criteria using TOPSIS algorithm

Table 5.1 clarifies which criteria represent cost functions (i.e. to minimize) and which stand for benefit functions (i.e. to maximize).

Cost	Benefit
Facility	% SoC provided
Energy	Charging Time
Waiting Time	
Service Time	
Battery Staytime	

Table 5.1 Cost and Benefit criteria

Let $X = (x_{ij})$ be the decision matrix and $W = [w_1, w_2, \dots, w_n]$ the weighted vector, where $x_{ij}, w_j \in \mathfrak{R}$ and $\sum_{j=1}^{n} w_j \ = 1$ with w_j the weight of the j-th criterion.

Since the criteria are measured in various units (second, kWh, etc.), the scores in the evaluation matrix X have to be transformed to a normalized scale. The normalization of decision matrix's values is carried out by the following standardized formula:

$$\overline{x_{ij}} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \qquad \text{for } i = 1, \dots, 18;\ j = 1, \dots, 14$$

Indices i and j refer to alternatives and criteria respectively. The weighted normalized value v_{ij} is calculated in this way:

$$v_{ij} = \overline{x_{ij}}\, w_j$$

At this point, the ideal positive solution and the negative ideal solution are identified: the first is the solution that maximizes the benefit criteria and minimizes the cost criteria whereas the second maximizes the cost criteria and minimizes the benefit criteria.

$$V^+ = positive\ ideal\ solution = \left[\left(\max v_{ij} \mid j\ \in C\right), \left(\min v_{ij} \mid j\ \in D\right)\right]$$

$$V^- = negative\ ideal\ solution = \left[\left(\min v_{ij} \mid j\ \in C\right), \left(\max v_{ij} \mid j\ \in D\right)\right]$$

Where C is associated with benefit criteria and D with the cost criteria.
The separation of each alternative from the positive ideal solution and from the negative ideal solution are given as the Euclidean distance:

$$S_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2} \qquad\qquad S_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}$$

The relative closeness of the alternatives with respect to V^+ is defined as:

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

Where $0 \leq P_i \leq 1$.
Finally, the set of alternatives can be ranked by the descending order of P_i value.

The identified solutions, obtained through the *TOPSIS* method explained before, are as close as possible to the ideal solution and are divided for expected SoC value as shown in Tables 5.2, 5.3 and 5.4 below.

Solving MCDA problem using TOPSIS Method

Configurations with expected SoC value = 20%

	NON BENEFIT				BENEFIT		NON BENEFIT				NON BENEFIT		BENEFIT	
	Costs				Quality of Service						Battery Preservation			
	0,3				0,6						0,1			
Criteria	Facility			Energy	% SoC		Waiting Time		Service Time		Battery Staytime		Charging time	
	0,5			0,5	0,4		0,5		0,1		0,2		0,8	
	No. of Workstat.	No. AGVs	No. of stations	TotEnergy	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
	0,2	0,1	0,7	1	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3
Weights	0,03	0,015	0,105	0,15	0,168	0,072	0,21	0,09	0,042	0,018	0,014	0,006	0,056	0,024
60,1,1	1	1	60	16616,562	85,340	9,272	271,738	350,294	89,518	4,680	2329,236	2982,698	5422,040	2014,824
60,2,1	2	1	60	16689,400	85,534	8,894	645,114	624,260	187,756	49,870	2343,908	2930,214	5447,430	2024,510
60,3,1	3	1	60	16709,516	85,588	8,812	763,536	667,664	299,614	87,232	2356,260	2918,890	5455,982	2030,172
60,2,2	2	2	60	16591,400	85,272	9,366	141,806	222,184	134,176	51,510	2325,170	3004,390	5412,668	2008,006
60,3,2	3	2	60	16628,406	85,370	9,244	235,926	346,938	200,036	107,144	2327,360	2967,854	5427,738	2019,198
60,3,3	3	3	60	16538,664	85,392	9,222	22,892	71,680	135,880	71,304	2354,586	3037,756	5382,854	2047,266
65,1,1	1	1	65	15661,022	86,316	7,840	40,798	80,666	89,552	4,698	2772,358	3142,022	5548,400	2113,868
65,2,1	2	1	65	15697,214	86,420	7,652	197,872	290,418	152,812	58,576	2768,986	3095,230	5561,480	2128,284
65,3,1	3	1	65	15706,070	86,448	7,624	208,204	318,618	217,174	111,758	2769,516	3084,040	5565,378	2132,956
65,2,2	2	2	65	15652,198	86,288	7,906	4,208	24,636	100,498	27,806	2773,572	3151,218	5544,868	2114,516
65,3,2	3	2	65	15663,184	86,322	7,826	19,978	72,180	141,534	78,696	2766,934	3136,018	5547,198	2114,552
65,3,3	3	3	65	15651,780	86,792	7,286	0,000	0,000	93,924	13,290	2772,228	3072,076	5539,600	2161,028
70,1,1	1	1	70	14808,420	87,304	6,574	0,282	1,446	89,578	4,640	3199,098	3273,492	5664,426	2220,326
70,2,1	2	1	70	14807,260	87,302	6,466	28,634	64,440	131,304	48,950	3186,560	3271,998	5664,128	2211,158
70,3,1	3	1	70	14813,930	87,324	6,400	30,764	90,790	171,818	90,714	3182,220	3265,088	5666,466	2210,364
70,2,2	2	2	70	14807,736	87,304	6,576	0,000	0,000	88,334	6,528	3197,744	3275,390	5663,940	2219,774
70,3,2	3	2	70	14805,360	87,298	6,582	0,000	0,000	93,040	8,842	3195,934	3275,440	5663,172	2219,398
70,3,3	3	3	70	14807,422	87,302	6,576	0,000	0,000	90,258	7,074	3198,130	3273,112	5664,052	2220,056

	NON BENEFIT				BENEFIT		NON BENEFIT				NON BENEFIT		BENEFIT	
	Costs				Quality of Service						Battery Preservation			
	0,3				0,6						0,1			
Criteria	Facility			Energy	% SoC		Waiting Time		Service Time		Battery Staytime		Charging time	
	0,5			0,5	0,4		0,5		0,1		0,2		0,8	
	No. of Workstat.	No. AGVs	No. of stations	TotEnergy	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
	0,2	0,1	0,7	1	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3
Weights	0,03	0,015	0,105	0,15	0,168	0,072	0,21	0,09	0,042	0,018	0,014	0,006	0,056	0,024
60,1,1	0,09623	0,12910	0,21714	0,24913	0,23284	0,27808	0,24446	0,30220	0,14042	0,01861	0,19680	0,22516	0,23037	0,22356
60,2,1	0,19245	0,12910	0,21714	0,25023	0,23337	0,26675	0,58035	0,53855	0,29452	0,19831	0,19804	0,22120	0,23144	0,22463
60,3,1	0,28868	0,12910	0,21714	0,25053	0,23352	0,26429	0,68688	0,57599	0,46999	0,34688	0,19908	0,22034	0,23181	0,22526
60,2,2	0,19245	0,25820	0,21714	0,24876	0,23266	0,28090	0,12757	0,19168	0,21047	0,20483	0,19646	0,22680	0,22997	0,22280
60,3,2	0,28868	0,25820	0,21714	0,24931	0,23293	0,27724	0,21224	0,29930	0,31379	0,42606	0,19664	0,22404	0,23061	0,22404
60,3,3	0,28868	0,38730	0,21714	0,24797	0,23299	0,27658	0,02059	0,06184	0,21315	0,28354	0,19894	0,22932	0,22870	0,22716
65,1,1	0,09623	0,12910	0,23524	0,23481	0,23551	0,23514	0,03670	0,06959	0,14048	0,01868	0,23424	0,23719	0,23573	0,23455
65,2,1	0,19245	0,12910	0,23524	0,23535	0,23579	0,22950	0,17801	0,25054	0,23971	0,23293	0,23396	0,23365	0,23629	0,23615
65,3,1	0,28868	0,12910	0,23524	0,23548	0,23587	0,22866	0,18730	0,27487	0,34067	0,44441	0,23400	0,23281	0,23646	0,23666
65,2,2	0,19245	0,25820	0,23524	0,23467	0,23543	0,23711	0,00379	0,02125	0,15765	0,11057	0,23434	0,23788	0,23558	0,23462
65,3,2	0,28868	0,25820	0,23524	0,23484	0,23552	0,23472	0,01797	0,06227	0,22202	0,31294	0,23378	0,23673	0,23568	0,23462
65,3,3	0,28868	0,38730	0,23524	0,23467	0,23681	0,21852	0,00000	0,00000	0,14733	0,05285	0,23423	0,23191	0,23536	0,23978
70,1,1	0,09623	0,12910	0,25333	0,22202	0,23820	0,19717	0,00025	0,00125	0,14052	0,01845	0,27030	0,24711	0,24066	0,24636
70,2,1	0,19245	0,12910	0,25333	0,22201	0,23820	0,19393	0,02576	0,05559	0,20597	0,19465	0,26924	0,24700	0,24065	0,24534
70,3,1	0,28868	0,12910	0,25333	0,22211	0,23826	0,19195	0,02768	0,07832	0,26952	0,36073	0,26887	0,24648	0,24075	0,24525
70,2,2	0,19245	0,25820	0,25333	0,22201	0,23820	0,19723	0,00000	0,00000	0,13856	0,02596	0,27018	0,24725	0,24064	0,24630
70,3,2	0,28868	0,25820	0,25333	0,22198	0,23819	0,19741	0,00000	0,00000	0,14595	0,03516	0,27003	0,24726	0,24061	0,24626
70,3,3	0,28868	0,38730	0,25333	0,22201	0,23820	0,19723	0,00000	0,00000	0,14158	0,02813	0,27022	0,24708	0,24065	0,24633

Performance score

	NON BENEFIT				BENEFIT		NON BENEFIT				NON BENEFIT		BENEFIT					
	Costs				Quality Service						Battery Preservation							
	0,3				0,6						0,1							
Criteria	Facility			Energy	% SoC		Waiting Time		Service Time		Battery Staytime		Charging time					
	0,5			0,5	0,4		0,5		0,1		0,2		0,8					
	No. of Workstat.	No. AGVs	No. of stations	TotEnergy	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.				
	0,2	0,1	0,7	1	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3				
Weights	0,03	0,015	0,105	0,15	0,168	0,072	0,21	0,09	0,042	0,018	0,014	0,006	0,056	0,024	S_i^+	S_i^-	P_i	Rank
60,1,1	0,00289	0,00194	0,02280	0,03737	0,03912	0,02002	0,05134	0,02720	0,00590	0,00033	0,00276	0,00135	0,01290	0,00537	0,05825	0,09794	0,62705	16
60,2,1	0,00577	0,00194	0,02280	0,03753	0,03921	0,01921	0,12187	0,04847	0,01237	0,00357	0,00277	0,00133	0,01296	0,00539	0,13147	0,02557	0,16281	17
60,3,1	0,00866	0,00194	0,02280	0,03758	0,03923	0,01903	0,14425	0,05184	0,01974	0,00624	0,00279	0,00132	0,01298	0,00541	0,15420	0,00779	0,04811	18
60,2,2	0,00577	0,00387	0,02280	0,03731	0,03909	0,02023	0,02679	0,01725	0,00884	0,00369	0,00275	0,00136	0,01288	0,00535	0,03264	0,12328	0,79066	12
60,3,2	0,00866	0,00387	0,02280	0,03740	0,03913	0,01996	0,04457	0,02694	0,01318	0,00767	0,00275	0,00134	0,01291	0,00538	0,05362	0,10322	0,65812	15
60,3,3	0,00866	0,00581	0,02280	0,03719	0,03914	0,01991	0,00432	0,00557	0,00895	0,00510	0,00279	0,00138	0,01281	0,00545	0,01214	0,14797	0,92419	10
65,1,1	0,00289	0,00194	0,02470	0,03522	0,03957	0,01693	0,00771	0,00626	0,00590	0,00034	0,00328	0,00142	0,01320	0,00563	0,01084	0,14504	0,93047	7
65,2,1	0,00577	0,00194	0,02470	0,03530	0,03961	0,01652	0,03738	0,02255	0,01007	0,00419	0,00328	0,00140	0,01323	0,00567	0,04437	0,11147	0,71527	13
65,3,1	0,00866	0,00194	0,02470	0,03532	0,03963	0,01646	0,03933	0,02474	0,01431	0,00800	0,00328	0,00140	0,01324	0,00568	0,04843	0,10864	0,69165	14
65,2,2	0,00577	0,00387	0,02470	0,03520	0,03955	0,01707	0,00079	0,00191	0,00662	0,00199	0,00328	0,00143	0,01319	0,00563	0,00613	0,15268	0,96138	1
65,3,2	0,00866	0,00387	0,02470	0,03523	0,03957	0,01690	0,00377	0,00560	0,00932	0,00563	0,00327	0,00142	0,01320	0,00563	0,01192	0,14835	0,92561	9
65,3,3	0,00866	0,00581	0,02470	0,03520	0,03978	0,01573	0,00000	0,00000	0,00619	0,00095	0,00328	0,00139	0,01318	0,00575	0,00876	0,15408	0,94621	4
70,1,1	0,00289	0,00194	0,02660	0,03330	0,04002	0,01420	0,00005	0,00011	0,00590	0,00033	0,00378	0,00148	0,01348	0,00591	0,00720	0,15423	0,95537	2
70,2,1	0,00577	0,00194	0,02660	0,03330	0,04002	0,01396	0,00541	0,00500	0,00865	0,00350	0,00377	0,00148	0,01348	0,00589	0,01164	0,14716	0,92672	8
70,3,1	0,00866	0,00194	0,02660	0,03332	0,04003	0,01382	0,00581	0,00705	0,01132	0,00649	0,00376	0,00148	0,01348	0,00589	0,01554	0,14587	0,90372	11
70,2,2	0,00577	0,00387	0,02660	0,03330	0,04002	0,01420	0,00000	0,00000	0,00582	0,00047	0,00378	0,00148	0,01348	0,00591	0,00800	0,15420	0,95070	3
70,3,2	0,00866	0,00387	0,02660	0,03330	0,04002	0,01421	0,00000	0,00000	0,00613	0,00063	0,00378	0,00148	0,01347	0,00591	0,00943	0,15413	0,94234	5
70,3,3	0,00866	0,00581	0,02660	0,03330	0,04002	0,01420	0,00000	0,00000	0,00595	0,00051	0,00378	0,00148	0,01348	0,00591	0,01001	0,15414	0,93902	6
Positive Ideal Solution V^+	0,00289	0,00194	0,02280	0,03330	0,04003	0,02023	0,00000	0,00000	0,00582	0,00033	0,00275	0,00132	0,01348	0,00591				
V^- Negative ideal solution	0,00866	0,00581	0,02660	0,03758	0,03909	0,01382	0,14425	0,05184	0,01974	0,00800	0,00378	0,00148	0,01281	0,00535				

BEST ALTERNATIVE

Table 5.2 Optimal Solution for Expected SoC Value = 20%

Solving MCDM problem using TOPSIS Method

Configurations with expected SoC value = 25%

	NON BENEFIT				BENEFIT		NON BENEFIT				NON BENEFIT		BENEFIT	
	Costs				Quality of Service						Battery Preservation			
	0,3				0,6						0,1			
Criteria	Facility			Energy	% SoC		Waiting Time		Service Time		Battery Staytime		Charging time	
	0,5			0,5	0,4		0,5		0,1		0,2		0,8	
	No. of Workstat.	No. AGVs	No. of stations	TotEnergy	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
	0,2	0,1	0,7	1	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3
Weights	**0,03**	**0,015**	**0,105**	**0,15**	**0,168**	**0,072**	**0,21**	**0,09**	**0,042**	**0,018**	**0,014**	**0,006**	**0,056**	**0,024**
60,1,1	1	1	60	16795,098	85,498	8,848	672,762	600,324	89,548	4,748	2173,050	2838,494	5055,792	2142,052
60,2,1	2	1	60	16910,070	86,118	7,986	2274,212	1441,294	203,168	39,452	2347,978	2777,396	5136,304	2199,860
60,3,1	3	1	60	16868,674	86,304	7,744	2587,578	1665,778	314,768	75,012	2410,918	2785,838	5162,032	2219,076
60,2,2	2	2	60	16774,566	85,448	8,936	434,398	473,552	153,424	51,690	2156,728	2866,018	5049,188	2136,074
60,3,2	3	2	60	16801,160	85,514	8,774	685,180	600,012	271,556	85,356	2179,130	2822,574	5059,568	2134,658
60,3,3	3	3	60	16734,216	85,350	9,210	148,750	231,802	165,680	91,496	2148,306	2916,528	5035,198	2137,400
65,1,1	1	1	65	15787,612	86,454	7,692	226,890	297,892	89,550	4,778	2604,422	3071,158	5176,776	2247,114
65,2,1	2	1	65	15856,342	86,640	7,358	571,288	572,202	181,114	53,230	2615,648	3020,110	5197,448	2267,334
65,3,1	3	1	65	15865,736	86,668	7,344	637,808	586,570	292,494	90,452	2625,194	3009,214	5201,312	2265,668
65,2,2	2	2	65	15767,454	86,404	7,742	111,914	180,858	130,540	50,808	2600,180	3090,028	5169,220	2242,730
65,3,2	3	2	65	15795,490	86,476	7,698	192,712	289,002	195,132	106,010	2603,024	3057,412	5179,850	2255,394
65,3,3	3	3	65	15744,474	86,004	6,788	10,744	49,608	128,734	64,756	2613,780	3102,002	5151,718	2299,812
70,1,1	1	1	70	14940,910	87,288	6,428	36,652	72,406	89,534	4,702	3029,910	3215,178	5290,944	2341,906
70,2,1	2	1	70	14972,696	87,384	6,232	197,722	289,976	153,148	58,508	3028,374	3164,876	5295,312	2346,008
70,3,1	3	1	70	14980,442	87,404	6,198	204,810	312,882	217,242	111,752	3031,948	3156,316	5298,946	2351,776
70,2,2	2	2	70	14933,860	87,268	6,468	3,240	19,694	99,952	26,984	3030,756	3221,690	5288,070	2341,160
70,3,2	3	2	70	14942,008	87,292	6,416	16,664	64,446	139,534	76,900	3024,762	3206,004	5288,952	2344,076
70,3,3	3	3	70	14932,292	87,264	6,492	0,000	0,000	93,190	11,052	3031,710	3223,318	5287,562	2341,260

	NON BENEFIT				BENEFIT		NON BENEFIT				NON BENEFIT		BENEFIT	
	Costs				Quality of Service						Battery Preservation			
	0,3				0,6						0,1			
Criteria	Facility			Energy	% SoC		Waiting Time		Service Time		Battery Staytime		Charging time	
	0,5			0,5	0,4		0,5		0,1		0,2		0,8	
	No. of Workstat.	No. AGVs	No. of stations	TotEnergy	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
	0,2	0,1	0,7	1	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3
Weights	**0,03**	**0,015**	**0,105**	**0,15**	**0,168**	**0,072**	**0,21**	**0,09**	**0,042**	**0,018**	**0,014**	**0,006**	**0,056**	**0,024**
60,1,1	0,09623	0,12910	0,21714	0,24938	0,23300	0,27705	0,18033	0,22819	0,11678	0,01708	0,19358	0,22050	0,22981	0,22363
60,2,1	0,19245	0,12910	0,21714	0,25108	0,23469	0,25006	0,60961	0,54785	0,26496	0,14191	0,20916	0,21576	0,23347	0,22967
60,3,1	0,28868	0,12910	0,21714	0,25047	0,23519	0,24248	0,69360	0,63318	0,41050	0,26983	0,21477	0,21641	0,23464	0,23167
60,2,2	0,19245	0,25820	0,21714	0,24907	0,23286	0,27981	0,11644	0,18000	0,20008	0,18594	0,19212	0,22264	0,22951	0,22301
60,3,2	0,28868	0,25820	0,21714	0,24947	0,23304	0,27473	0,18366	0,22807	0,35414	0,30704	0,19412	0,21927	0,22998	0,22286
60,3,3	0,28868	0,38730	0,21714	0,24847	0,23259	0,28839	0,03987	0,08811	0,21607	0,32912	0,19137	0,22656	0,22887	0,22315
65,1,1	0,09623	0,12910	0,23524	0,23442	0,23560	0,24085	0,06082	0,11323	0,11678	0,01719	0,23200	0,23858	0,23531	0,23460
65,2,1	0,19245	0,12910	0,23524	0,23544	0,23611	0,23040	0,15313	0,21750	0,23620	0,19148	0,23300	0,23461	0,23625	0,23671
65,3,1	0,28868	0,12910	0,23524	0,23558	0,23619	0,22996	0,17097	0,22296	0,38145	0,32537	0,23385	0,23376	0,23642	0,23654
65,2,2	0,19245	0,25820	0,23524	0,23412	0,23547	0,24242	0,03000	0,06875	0,17024	0,18276	0,23163	0,24004	0,23496	0,23414
65,3,2	0,28868	0,25820	0,23524	0,23454	0,23566	0,24104	0,05166	0,10985	0,25448	0,38133	0,23188	0,23751	0,23545	0,23547
65,3,3	0,28868	0,38730	0,23524	0,23378	0,23438	0,21255	0,00288	0,01886	0,16789	0,23294	0,23284	0,24097	0,23417	0,24010
70,1,1	0,09623	0,12910	0,25333	0,22185	0,23788	0,20128	0,00982	0,02752	0,11676	0,01691	0,26991	0,24976	0,24050	0,24450
70,2,1	0,19245	0,12910	0,25333	0,22232	0,23814	0,19514	0,05300	0,11022	0,19972	0,21046	0,26977	0,24586	0,24070	0,24493
70,3,1	0,28868	0,12910	0,25333	0,22243	0,23819	0,19407	0,05490	0,11893	0,28331	0,40199	0,27009	0,24519	0,24086	0,24553
70,2,2	0,19245	0,25820	0,25333	0,22174	0,23782	0,20253	0,00087	0,00749	0,13035	0,09707	0,26998	0,25027	0,24037	0,24442
70,3,2	0,28868	0,25820	0,25333	0,22186	0,23789	0,20090	0,00447	0,02450	0,18197	0,27662	0,26945	0,24905	0,24041	0,24473
70,3,3	0,28868	0,38730	0,25333	0,22172	0,23781	0,20328	0,00000	0,00000	0,12153	0,03976	0,27007	0,25040	0,24034	0,24443

	NON BENEFIT				BENEFIT		NON BENEFIT				NON BENEFIT		BENEFIT					
	Costs				Quality Service						Battery Preservation							
	0,3				0,6						0,1							
Criteria	Facility			Energy	% SoC		Waiting Time		Service Time		Battery Staytime		Charging time					
	0,5			0,5	0,4		0,5		0,1		0,2		0,8				Performance score	
	No. of Workstat.	No. AGVs	No. of stations	TotEnergy	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.				
	0,2	0,1	0,7	1	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3				
Weights	**0,03**	**0,015**	**0,105**	**0,15**	**0,168**	**0,072**	**0,21**	**0,09**	**0,042**	**0,018**	**0,014**	**0,006**	**0,056**	**0,024**	S_i^+	S_i^-	P_i	**Rank**
60,1,1	0,00289	0,00194	0,02280	0,03741	0,03914	0,01995	0,03787	0,02054	0,00490	0,00031	0,00271	0,00132	0,01287	0,00537	0,04330	0,11509	0,72661	**14**
60,2,1	0,00577	0,00194	0,02280	0,03766	0,03943	0,01800	0,12802	0,04931	0,01113	0,00255	0,00293	0,00129	0,01307	0,00551	0,13748	0,02201	0,13800	**17**
60,3,1	0,00866	0,00194	0,02280	0,03757	0,03951	0,01746	0,14566	0,05699	0,01724	0,00486	0,00301	0,00130	0,01314	0,00556	0,15716	0,00695	**0,04232**	**18**
60,2,2	0,00577	0,00387	0,02280	0,03736	0,03912	0,02015	0,02445	0,01620	0,00840	0,00335	0,00269	0,00134	0,01285	0,00535	0,03021	0,12850	0,80965	**12**
60,3,2	0,00866	0,00387	0,02280	0,03742	0,03915	0,01978	0,03857	0,02053	0,01487	0,00553	0,00272	0,00132	0,01288	0,00535	0,04574	0,11340	0,71256	**16**
60,3,3	0,00866	0,00581	0,02280	0,03727	0,03908	0,02076	0,00837	0,00793	0,00907	0,00592	0,00268	0,00136	0,01282	0,00536	0,01575	0,14623	0,90277	**7**
65,1,1	0,00289	0,00194	0,02470	0,03516	0,03958	0,01734	0,01277	0,01019	0,00490	0,00031	0,00325	0,00143	0,01318	0,00563	0,01693	0,14184	0,89337	**8**
65,2,1	0,00577	0,00194	0,02470	0,03532	0,03967	0,01659	0,03216	0,01957	0,00992	0,00345	0,00326	0,00141	0,01323	0,00568	0,03856	0,11996	0,75676	**13**
65,3,1	0,00866	0,00194	0,02470	0,03534	0,03968	0,01656	0,03590	0,02007	0,01602	0,00586	0,00327	0,00140	0,01324	0,00568	0,04365	0,11595	0,72648	**15**
65,2,2	0,00577	0,00387	0,02470	0,03512	0,03956	0,01745	0,00630	0,00619	0,00715	0,00329	0,00324	0,00144	0,01316	0,00562	0,01108	0,14884	**0,93072**	**6**
65,3,2	0,00866	0,00387	0,02470	0,03518	0,03959	0,01736	0,01085	0,00989	0,01069	0,00686	0,00325	0,00143	0,01319	0,00565	0,01867	0,14304	0,88454	**10**
65,3,3	0,00866	0,00581	0,02470	0,03507	0,03938	0,01530	0,00060	0,00170	0,00705	0,00419	0,00326	0,00145	0,01311	0,00576	0,01044	0,15564	0,93715	**4**
70,1,1	0,00289	0,00194	0,02660	0,03328	0,03996	0,01449	0,00206	0,00248	0,00490	0,00030	0,00378	0,00150	0,01347	0,00587	0,00809	0,15447	0,95024	**1**
70,2,1	0,00577	0,00194	0,02660	0,03335	0,04001	0,01405	0,01113	0,00992	0,00839	0,00379	0,00378	0,00148	0,01348	0,00588	0,01777	0,14299	0,88948	**9**
70,3,1	0,00866	0,00194	0,02660	0,03337	0,04002	0,01397	0,01153	0,01070	0,01190	0,00724	0,00378	0,00147	0,01349	0,00589	0,02097	0,14211	0,87143	**11**
70,2,2	0,00577	0,00387	0,02660	0,03326	0,03995	0,01458	0,00018	0,00067	0,00547	0,00175	0,00378	0,00150	0,01346	0,00587	0,00830	0,15664	0,94968	**2**
70,3,2	0,00866	0,00387	0,02660	0,03328	0,03996	0,01446	0,00094	0,00220	0,00764	0,00498	0,00377	0,00149	0,01346	0,00587	0,01129	0,15513	0,93214	**5**
70,3,3	0,00866	0,00581	0,02660	0,03326	0,03995	0,01464	0,00000	0,00000	0,00510	0,00072	0,00378	0,00150	0,01346	0,00587	0,01009	0,15708	0,93965	**3**

BEST ALTERNATIVE

Positive Ideal Solution **V^+**	0,00289	0,00194	0,02280	0,03326	0,04002	0,02076	0,00000	0,00000	0,00490	0,00030	0,00268	0,00129	0,01349	0,00589
V^- Negative ideal solution	0,00866	0,00581	0,02660	0,03766	0,03908	0,01397	0,14566	0,05699	0,01724	0,00724	0,00378	0,00150	0,01282	0,00535

Table 5.3 Optimal Solution for Expected SoC Value = 25%

Solving MCDA problem using TOPSIS Method

Configurations with expected SoC value = 30%

	NON BENEFIT				BENEFIT		NON BENEFIT				NON BENEFIT		BENEFIT	
	Costs				Quality of Service						Battery Preservation			
	0,3				0,6						0,1			
Criteria	Facility			Energy	% SoC		Waiting Time		Service Time		Battery Staytime		Charging time	
	0,5			0,5	0,4		0,5		0,1		0,2		0,8	
	No. of Workstat.	No. AGVs	No. of stations	TotEnergy	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
	0,2	0,1	0,7	1	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3
Weights	0,03	0,015	0,105	0,15	0,168	0,072	0,21	0,09	0,042	0,018	0,014	0,006	0,056	0,024
60,1,1	1	1	60	17032,636	86,204	7,876	2274,298	1435,364	89,644	4,848	2144,916	2642,388	4795,448	2307,096
60,2,1	2	1	60	17067,842	87,068	6,704	4371,308	2735,212	205,796	36,434	2498,222	2728,758	4912,090	2392,666
60,3,1	3	1	60	16914,918	87,258	6,432	4679,206	3021,850	317,920	71,676	2592,042	2758,262	4939,622	2403,884
60,2,2	2	2	60	16774,566	85,448	8,936	434,398	473,552	153,424	51,690	2156,728	2866,018	4997,188	2136,074
60,3,2	3	2	60	16801,160	85,514	8,774	685,180	600,012	271,556	85,356	2179,130	2822,574	5011,568	2134,658
60,3,3	3	3	60	16835,730	85,380	8,884	446,324	552,546	171,478	86,334	2006,100	2703,302	4707,156	2257,280
65,1,1	1	1	65	16079,886	86,556	7,436	682,320	601,806	89,632	4,838	2388,762	2911,780	4834,592	2336,448
65,2,1	2	1	65	16183,126	87,108	6,620	2275,820	1440,406	203,126	39,488	2573,588	2844,822	4902,626	2394,356
65,3,1	3	1	65	16148,322	87,270	6,376	2576,936	1662,072	314,748	74,944	2638,464	2853,096	4924,922	2405,606
65,2,2	2	2	65	15767,454	86,404	7,742	111,914	180,858	130,540	50,808	2600,180	3090,028	4999,220	2242,730
65,3,2	3	2	65	15795,490	86,476	7,698	192,712	289,002	195,132	106,010	2603,024	3057,412	5051,850	2255,394
65,3,3	3	3	65	16016,322	86,626	6,920	164,728	250,132	138,128	92,564	2369,052	2970,472	4820,714	2371,134
70,1,1	1	1	70	15168,476	87,334	6,432	275,684	354,264	89,560	4,732	2807,092	3113,782	4940,022	2428,132
70,2,1	2	1	70	15236,070	87,516	6,104	653,362	625,988	187,238	50,984	2823,478	3066,244	4956,682	2449,770
70,3,1	3	1	70	15253,384	87,568	6,036	760,932	665,466	299,322	87,252	2838,590	3055,190	4966,218	2447,928
70,2,2	2	2	70	14933,860	87,268	6,468	3,240	19,694	99,952	26,984	2920,756	3221,690	4938,070	2341,160
70,3,2	3	2	70	14942,008	87,292	6,416	16,664	64,446	139,534	76,900	2914,762	3206,004	5038,952	2344,076
70,3,3	3	3	70	15108,162	87,390	5,950	20,156	67,650	97,168	71,766	2801,360	3159,058	4922,978	2429,308

	NON BENEFIT				BENEFIT		NON BENEFIT				NON BENEFIT		BENEFIT	
	Costs				Quality of Service						Battery Preservation			
	0,3				0,6						0,1			
Criteria	Facility			Energy	% SoC		Waiting Time		Service Time		Battery Staytime		Charging time	
	0,5			0,5	0,4		0,5		0,1		0,2		0,8	
	No. of Workstat.	No. AGVs	No. of stations	TotEnergy	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
	0,2	0,1	0,7	1	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3
Weights	0,03	0,015	0,105	0,15	0,168	0,072	0,21	0,09	0,042	0,018	0,014	0,006	0,056	0,024
60,1,1	0,09623	0,12910	0,21714	0,25059	0,23418	0,25904	0,29245	0,28198	0,10933	0,01764	0,19728	0,21087	0,22944	0,23243
60,2,1	0,19245	0,12910	0,21714	0,25111	0,23653	0,22049	0,56210	0,53735	0,25099	0,13259	0,22978	0,21776	0,23502	0,24105
60,3,1	0,28868	0,12910	0,21714	0,24886	0,23705	0,21155	0,60169	0,59366	0,38774	0,26083	0,23841	0,22012	0,23634	0,24218
60,2,2	0,19245	0,25820	0,21714	0,24679	0,23213	0,29390	0,05586	0,09303	0,18712	0,18810	0,19837	0,22871	0,23909	0,21520
60,3,2	0,28868	0,25820	0,21714	0,24718	0,23231	0,28858	0,08811	0,11788	0,33120	0,31062	0,20043	0,22525	0,23978	0,21506
60,3,3	0,28868	0,38730	0,21714	0,24769	0,23195	0,29219	0,05739	0,10855	0,20914	0,31417	0,18451	0,21573	0,22522	0,22741
65,1,1	0,09623	0,12910	0,23524	0,23657	0,23514	0,24457	0,08774	0,11823	0,10932	0,01761	0,21971	0,23237	0,23131	0,23539
65,2,1	0,19245	0,12910	0,23524	0,23809	0,23664	0,21773	0,29264	0,28298	0,24774	0,14370	0,23671	0,22702	0,23457	0,24122
65,3,1	0,28868	0,12910	0,23524	0,23758	0,23708	0,20971	0,33136	0,32652	0,38387	0,27273	0,24268	0,22768	0,23564	0,24235
65,2,2	0,19245	0,25820	0,23524	0,23198	0,23473	0,25463	0,01439	0,03553	0,15921	0,18489	0,23915	0,24659	0,23919	0,22594
65,3,2	0,28868	0,25820	0,23524	0,23239	0,23492	0,25319	0,02478	0,05678	0,23799	0,38578	0,23942	0,24399	0,24171	0,22722
65,3,3	0,28868	0,38730	0,23524	0,23564	0,23533	0,22760	0,02118	0,04914	0,16846	0,33685	0,21790	0,23705	0,23065	0,23888
70,1,1	0,09623	0,12910	0,25333	0,22316	0,23725	0,21155	0,03545	0,06960	0,10923	0,01722	0,25819	0,24849	0,23636	0,24462
70,2,1	0,19245	0,12910	0,25333	0,22416	0,23775	0,20076	0,08401	0,12298	0,22836	0,18553	0,25969	0,24469	0,23716	0,24680
70,3,1	0,28868	0,12910	0,25333	0,22441	0,23789	0,19852	0,09785	0,13073	0,36506	0,31751	0,26108	0,24381	0,23761	0,24662
70,2,2	0,19245	0,25820	0,25333	0,21971	0,23707	0,21273	0,00042	0,00387	0,12190	0,09820	0,26864	0,25710	0,23626	0,23586
70,3,2	0,28868	0,25820	0,25333	0,21983	0,23714	0,21102	0,00214	0,01266	0,17018	0,27984	0,26809	0,25585	0,24109	0,23615
70,3,3	0,28868	0,38730	0,25333	0,22228	0,23741	0,19570	0,00259	0,01329	0,11851	0,26116	0,25766	0,25210	0,23554	0,24474

Performance score

	NON BENEFIT				BENEFIT		NON BENEFIT				NON BENEFIT		BENEFIT					
	Costs				Quality Service						Battery Preservation							
	0,3				0,6						0,1							
Criteria	Facility			Energy	% SoC		Waiting Time		Service Time		Battery Staytime		Charging time					
	0,5			0,5	0,4		0,5		0,1		0,2		0,8					
	No. of Workstat.	No. AGVs	No. of stations	TotEnergy	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.				
	0,2	0,1	0,7	1	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3	0,7	0,3				
Weights	0,03	0,015	0,105	0,15	0,168	0,072	0,21	0,09	0,042	0,018	0,014	0,006	0,056	0,024	S_i^+	S_i^-	P_i	Rank
60,1,1	0,00289	0,00194	0,02280	0,03759	0,03934	0,01865	0,06141	0,02538	0,00459	0,00032	0,00276	0,00127	0,01285	0,00558	0,06645	0,07259	0,52207	14
60,2,1	0,00577	0,00194	0,02280	0,03767	0,03974	0,01588	0,11804	0,04836	0,01054	0,00239	0,00322	0,00131	0,01316	0,00579	0,12774	0,01383	0,09767	17
60,3,1	0,00866	0,00194	0,02280	0,03733	0,03982	0,01523	0,12636	0,05343	0,01629	0,00469	0,00334	0,00132	0,01323	0,00581	0,13786	0,00614	0,04263	18
60,2,2	0,00577	0,00387	0,02280	0,03702	0,03900	0,02116	0,01173	0,00837	0,00786	0,00339	0,00278	0,00137	0,01339	0,00516	0,01582	0,12382	0,88671	8
60,3,2	0,00866	0,00387	0,02280	0,03708	0,03903	0,02078	0,01850	0,01061	0,01391	0,00559	0,00281	0,00135	0,01343	0,00516	0,02480	0,11635	0,82432	12
60,3,3	0,00866	0,00581	0,02280	0,03715	0,03897	0,02104	0,01205	0,00977	0,00878	0,00566	0,00258	0,00129	0,01261	0,00546	0,01860	0,12286	0,86848	9
65,1,1	0,00289	0,00194	0,02470	0,03549	0,03950	0,01761	0,01843	0,01064	0,00459	0,00032	0,00308	0,00139	0,01295	0,00565	0,02158	0,11718	0,84448	10
65,2,1	0,00577	0,00194	0,02470	0,03571	0,03976	0,01568	0,06146	0,02547	0,01040	0,00259	0,00331	0,00136	0,01314	0,00579	0,06698	0,07129	0,51558	15
65,3,1	0,00866	0,00194	0,02470	0,03564	0,03983	0,01510	0,06959	0,02939	0,01612	0,00491	0,00340	0,00137	0,01320	0,00582	0,07687	0,06189	0,44601	16
65,2,2	0,00577	0,00387	0,02470	0,03480	0,03943	0,01833	0,00302	0,00320	0,00669	0,00333	0,00335	0,00148	0,01339	0,00542	0,00765	0,13373	0,94590	1
65,3,2	0,00866	0,00387	0,02470	0,03486	0,03947	0,01823	0,00520	0,00511	0,01000	0,00694	0,00335	0,00146	0,01354	0,00545	0,01327	0,13071	0,90783	7
65,3,3	0,00866	0,00581	0,02470	0,03535	0,03954	0,01639	0,00445	0,00442	0,00708	0,00606	0,00305	0,00142	0,01292	0,00573	0,01250	0,13177	0,91337	6
70,1,1	0,00289	0,00194	0,02660	0,03347	0,03986	0,01523	0,00744	0,00626	0,00459	0,00031	0,00361	0,00149	0,01324	0,00587	0,01184	0,12890	0,91587	5
70,2,1	0,00577	0,00194	0,02660	0,03362	0,03994	0,01445	0,01764	0,01107	0,00959	0,00334	0,00364	0,00147	0,01328	0,00592	0,02295	0,11710	0,83613	11
70,3,1	0,00866	0,00194	0,02660	0,03366	0,03997	0,01429	0,02055	0,01177	0,01533	0,00572	0,00366	0,00146	0,01331	0,00592	0,02811	0,11387	0,80200	13
70,2,2	0,00577	0,00387	0,02660	0,03296	0,03983	0,01532	0,00009	0,00035	0,00512	0,00177	0,00376	0,00154	0,01323	0,00566	0,00805	0,13766	0,94478	2
70,3,2	0,00866	0,00387	0,02660	0,03297	0,03984	0,01519	0,00045	0,00114	0,00715	0,00504	0,00375	0,00154	0,01350	0,00567	0,01088	0,13676	0,92632	3
70,3,3	0,00866	0,00581	0,02660	0,03334	0,03988	0,01409	0,00054	0,00120	0,00498	0,00470	0,00361	0,00151	0,01319	0,00587	0,01160	0,13678	0,92184	4

BEST ALTERNATIVE

Positive Ideal Solution V^+	0,00289	0,00194	0,02280	0,03296	0,03997	0,02116	0,00009	0,00035	0,00459	0,00031	0,00258	0,00127	0,01354	0,00592
V^- Negative ideal solution	0,00866	0,00581	0,02660	0,03767	0,03897	0,01409	0,12636	0,05343	0,01629	0,00694	0,00376	0,00154	0,01261	0,00516

Table 5.4 Optimal Solution for Expected SoC Value = 30%

Therefore, the best alternative for expected SoC value 20% and 30% is the one with 65 stations, 2 AGVs and 2 workstations, while for expected SoC value 25% is the one with 70 stations, 1 AGV and 1 workstation. Independently of where it is located in Turin, each station is assumed to have the same layout.

5.8 The Impact on the Power System

It is interesting to observe the energy behavior of the system since significant considerations can be derived. In this regard, it is worthwhile to evaluate the values of energy taken from the electricity grid in relation to electricity consumption to measure the impact that such stations may have on the existing electricity distribution network. The energy consumption required by a single BSS to recharge the batteries in a single day, considering the worst case in which the expected SoC value is 30% (i.e. there are more cars that require battery exchange), is on average 16 thousand kWh, i.e. 16 MWh. In the optimal configurations chosen (see previous section), the results obtained suggest that the annual energy consumed to recharge the battery packs, in the 65 stations planned in Turin, will be given by the following formulas in which it is assumed, as a worst-case scenario, that each station remains open and operational 365 days a year, 24 hours a day:

$$16\ MWh/day * 365\ day = 5840\ MWh/year$$

$$5840\ MWh/year\ * 65\ stations = 379\,600\ MWh/year$$

Subsequently, taking into consideration the data on energy produced from renewable sources in Turin and its province in 2017, which is 3.536 TWh and corresponds to 3.4% of what is produced in Italy (104 TWh) [40], and comparing the result just obtained it is clear that it accounts for only about 11% of all energy production. This clearly demonstrates the feasibility, suitability and sustainability of this project. If we would like to make a further comparison with the production of electricity from renewable sources in Piedmont in the same year (9.717 TWh) [40], this ratio is reduced to 4%. As a result of the calculations carried out through this study, it was found that in energy terms, the impact of such a charging infrastructure on the power grid would still be marginal. This is also due to the fact that the designed stations do not use fast charging but the chargers are limited to a power of 22 kW.

In Chapter 3, it was assumed to convert the entire fleet of vehicles of Turin into electric cars. About this, it is now possible to make a comparison between internal combustion vehicles (ICE) and electric vehicles (EV) from the point of view of the energy spent on feeding these two types of vehicles.
Taking as reference the study case analyzed in this work, on average about 16 MWh of energy was used by one BSS to charge electric cars. On the other hand, to supply the same number of internal combustion (ICE) vehicles would have required instead an energy almost three times higher: 46 MWh (calculations made based also on data provided by [41]). This is essentially due to the difference between the two energy production lines.
As reported by Enel's data [42], for a gasoline car, the energy extraction process is divided into the following phases: oil refining, transport and conversion into mechanical energy of gasoline through the engine. The result is an overall efficiency of 18-19%.
At the same time, for an electric car, the energy analysis passes through the following steps: electricity production, transmission along the grid, transformation of the electrical energy stored in the batteries into mechanical energy through the motor. In this case, the efficiency reaches 52% [42]. In short, EVs are three times as efficient as ICE vehicles.

As a complementary verification and validation of the EVs' energy data obtained in this thesis work, the specific energy consumption per kilometer for electric cars has been computed and compared with that of ICE vehicles. From the best solutions found with the TOPSIS method, dividing the average total station energy by the Weighted Average per km of Range Recharged (WARR), 0.14 kWh/km is achieved:

$$\text{WARR} = (\%T * NCB * RangeRechargedT) + (\%R * NCB * RangeRechargedR)$$

Where:

- *%T*: is the percentage of distribution of Tesla Model 3 cars (1/3)
- *%R*: is the percentage of distribution of Renault Zoe cars (2/3)
- *NCB*: is the total number of charged batteries
- *RangeRechargedT*: is the Tesla's restored range in km
- *RangeRechargedR*: is the Renault's restored range in km

$$16\ MWh\ /\ WARR = 0.14\ kWh/km$$

This outcome is consistent with that obtained from the research conducted by the Energy & Strategy Group in collaboration with the Polytechnic of Milan [43], which indicates an average consumption of 0.15 kWh/km for a fully electric car.
Using fossil fuels such as gasoline or diesel instead, higher consumptions are obtained.
To make a homogeneous comparison with traditional vehicles it is necessary to know how many kWh of energy are contained in a liter of diesel or gasoline. In particular, 1

liter of diesel has an energy content of about 10 kWh, while 1 liter of gasoline contains about 8.9 kWh of energy. For instance, as regards gasoline cars, knowing that they consume on average about 45 kWh per 100 kilometers, the average consumption turns out to be of 0.45 kWh/km.
However, as evidenced by this comparison, the ratio remains constant and in favor of electric vehicles. Especially, the ratio of energy consumption of EVs to ICE vehicles is one to three (that is, 1:3).

In the Italian transport system there are currently 14 647 electric vehicles in circulation on a vehicle fleet of about 39 thousand cars, equivalent to a market penetration of 0.04%[17]. In the intermediate scenario of the study elaborated by The European House – Ambrosetti for Enel and Enel Foundation [44], by 2030, the estimate is to reach 5 million (14% of registrations). However, growth prospects have to deal with the impact of power consumption on the electricity system.
Starting from these last data, based on the reasoning supported by the research of the Energy & Strategy Group [43], it is estimated that, assuming an average annual distance of 11.000 km and an average consumption of 15 kWh/100 km, the average annual consumption of a full electric vehicle is about 1760 kWh. This value amounts to nearly half of the consumption of an average Italian family per year. The study [43] underlines that the total estimated consumption of the 7340 BEVs present at the end of last year in Italy is about 11.3 GWh/year, i.e. the 0.0035% of the national electricity consumption (320 TWh). As one may guess from the exiguous percentage, nothing to worry about it. Now, assuming a number of electric vehicles equal to 4.8 million, as in the moderate development scenario forecast for 2030 by the same study [43], and the same average consumption presented before, the total demand for electricity would be 8.4 TWh/year, which corresponds to about 2.5% of current electricity consumption in Italy. Therefore, the impact that an increase in the number of electric vehicles in circulation would have on the capacity of electricity distribution systems to support the power flows necessary for recharging is not so alarming.

What could actually can have a negative impact on the electrical grid is the huge amount of power required.
Figure 5.30 shows the power requirement during the day of a single station in the optimal configuration with 65 stations, 2 AGVs and 2 workstations in which an expected SoC value of 30% is estimated. It is clear that the power reaches its peak (around 1078 kW) between 09:00 and 10:00 and also at 20:00 for satisfying the battery swap demands.

[17] Re-elaboration of data from UNRAE

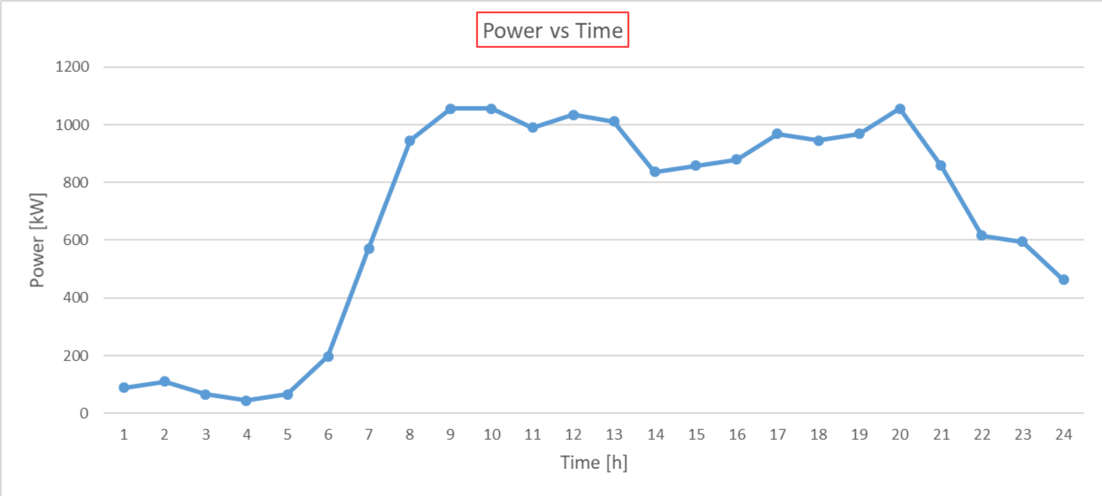


Figure 5.30 Power vs Time in the configuration 65, 2, 2 with expected SoC = 30%

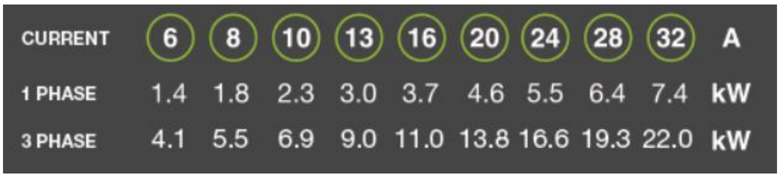
This peak power value, considering all 65 stations, is $1078\,kW * 65 \approx 70\,MW$ and it represents approximately 4.3% of the installed power from renewable sources in Turin and its province in 2017 (about 1.65 GW) [40]. As can be seen, the power involved in charging using chargers with a maximum power of 22 kW is not critical for the distribution lines. Conversely, a very different result it is achieved with regard to the fast recharge.

As a matter of fact, continues the study [43], if we consider an average charging power for fast charging spots of 100 kW and that 0.5% of vehicles (185 000) have to recharge simultaneously with a fast socket, the committed power would result in 18.5 GW. With reference to the maximum Italian committed power by renewable energy sources, which is around 53.26 GW [40], the value just found constitutes an increase of more than 34%, which means that the distribution lines, the transformers and the power plants need to handle enormous peaks of electrical demand when cars plug in. The current way of managing the urban power grid will face challenges and opportunities to adapt to the increase in EVs.

5.9 Further Improvement

As last step, to increase the system's efficiency, a further optimization is suggested.

Since there are chargers with adjustable charging current (from a minimum to a maximum value) where it is possible to choose the charging power according to the needs and so minimizing the risk of overload and increasing battery life, a smart type of charger that can vary the power based on demand can be employed in the BSS. These chargers, equipped with both a remote control system and a compatible monitoring system, can automatically adjust the charging current (and so the power). The following images (Figures 5.31 and 5.32) show an example of an adjustable EVR3W charger with power consumption (kW) in both three-phase and single-phase versions for each selectable current level (A):



CURRENT	6	8	10	13	16	20	24	28	32	A
1 PHASE	1.4	1.8	2.3	3.0	3.7	4.6	5.5	6.4	7.4	kW
3 PHASE	4.1	5.5	6.9	9.0	11.0	13.8	16.6	19.3	22.0	kW

Figure 5.31 Range of current and power values [45]

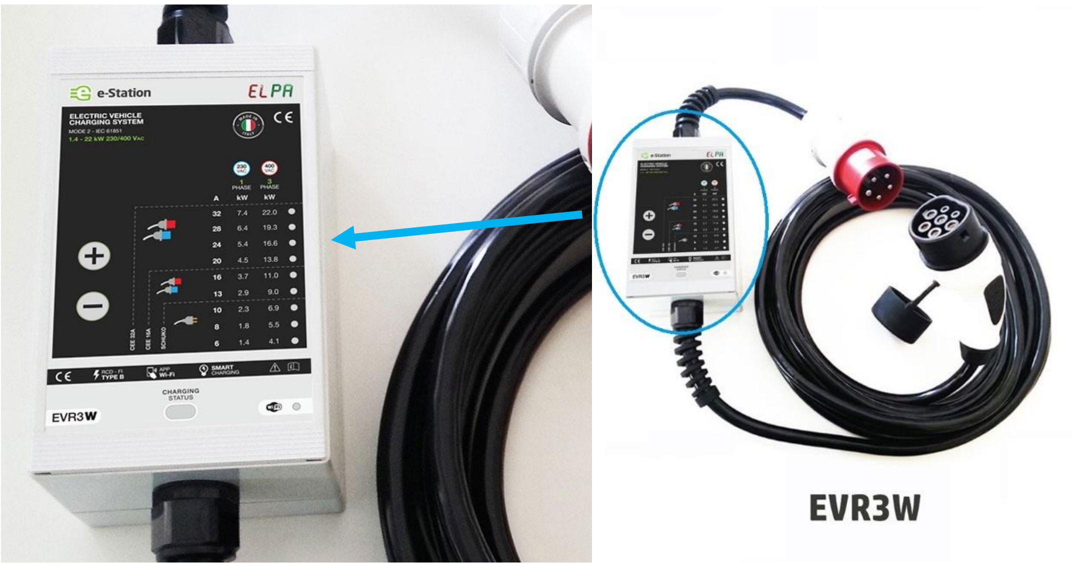


Figure 5.32 Detail of the EVR3W charger [45]

This is the most advanced solution on the market for charging electric vehicles because it allows automatic adjustment of the charging power. In this way, each battery can be recharged within the available capacity limits of the station's power system. The BSS’s warehouse will vary the power of the chargers depending on the urgency of the swapping orders, trying to minimize the damage incurred to the batteries if high charging rates are used. In other words, the chargers’ power is not fixed but varies according to system utilization (the more it is used, the more the power increases). As a result, if there is a lot of demand fast charging will be used, otherwise slow charges will be preferred to avoid further stressing the batteries. It is worth recalling that, in general, as the charging power increases, charging times are reduced to the detriment of the health of the battery.

For this purpose, an example code that dynamically modifies the power (using only 3 power values) of the chargers in the warehouse, based on two SoC’s threshold values, is provided. These two thresholds are set as global variables and are called *LowThresh* and *HighThresh*. The value that is compared with these two thresholds is the average SoC of the batteries exiting the rack (*SoCmean*), which is computed every time a battery leaves the warehouse. Also the 3 power values are set as global variables (*MinPow*, *MeanPow* and *MaxPow*) so that they can be changed in the future.

```
/*Custom Code*/
// Change the power values according to threshold values
Object current = param(1);
treenode activity = param(2);
Token token = param(3);
treenode processFlow = ownerobject(activity);

double SoCmean = 0;
double add = token.SwappedBattery.SoC;
sumexit ++;
total += add;
SoCmean = total/sumexit;

if (SoCmean >= HighTresh){
	for(int i = 1; i <= Table("PowerTable").numCols; i++){
		for(int j = 1; j <= Table("PowerTable").numRows; j++){
			Table("PowerTable")[j][i] = MinPow;
		}
	}
}

if (SoCmean < HighTresh && SoCmean >= LowTresh){
	for(int i = 1; i <= Table("PowerTable").numCols; i++){
		for(int j = 1; j <= Table("PowerTable").numRows; j++){
			Table("PowerTable")[j][i] = MeanPow;
		}
	}
}

if (SoCmean < LowTresh){
	for(int i = 1; i <= Table("PowerTable").numCols; i++){
		for(int j = 1; j <= Table("PowerTable").numRows; j++){
			Table("PowerTable")[j][i] = MaxPow;
		}
	}
}
```

In this fashion not only the life cycle of the batteries increases, but also the peak power on the power grid for each station in operation is relieved. It is important to keep in mind that these types of charging stations (with automatically adjustable power) are quite complex, they have lower overall reliability and are significantly more expensive than those with fixed charging power.

6 Conclusion and Future Work

In order to reliably predict the performance achievable in the automatic service system examined, it was decided to use the FlexSim discrete event software. It has made it possible to evaluate the effectiveness of the control logics implemented, nevertheless, given the lack of elements and functions specifically designed for this type of systems, it is convenient to use more advanced and suitable software.
However, the goal of this work is twofold: it evaluate the efficiency of the battery swap system providing a methodology for handle EV batteries in a station that uses the battery swap method and it would like to be the starting point for a future development in which many other improvement can be integrated.

The hope is that the conclusions and the results obtained in this work can be very useful for companies that want to exploit this type of technology encouraging at the same time car manufacturers to adopt a standard battery pack format interchangeable between different models of car manufacturers, which is one of the main factors that does not contribute to the worldwide spread of the technique treated in this thesis work.

As soon as more data will be available, the proposed model could be extended and improved creating a more robust and large-scale model. By the way, a number of relevant topics not implemented need to be further investigated, including:

- The analysis of BSSs' positioning at strategic places in a country considering traffic network when choosing location (e.g. along the highway network or at the toll plazas or even along the thoroughfares linking suburbs and cities)

- Extending the model to also include a wider range of car types and thus battery packs and to include EVs fleet of public transport such as taxis, buses or even electric car sharing services

- Implementing some variables and parameters that have been left out like the battery's State of Health (SoH), the battery's Depth of Discharge (DoD), battery life cycles, and so on

- Creation of a software or an app for smartphones capable of interacting with the Battery Swap Station from both the customer's and the station owner's point of view, for instance, checking the presence of charged batteries of a specific type in a station, etc.

Ultimately, whilst it is true that battery swapping solution has to face several obstacles in the private car sector because of the existence of a conservative and deep-rooted “car culture” that considers the car as something strictly personal, it can provide more benefits for urban public transport as an ancillary service for electric buses and taxis.

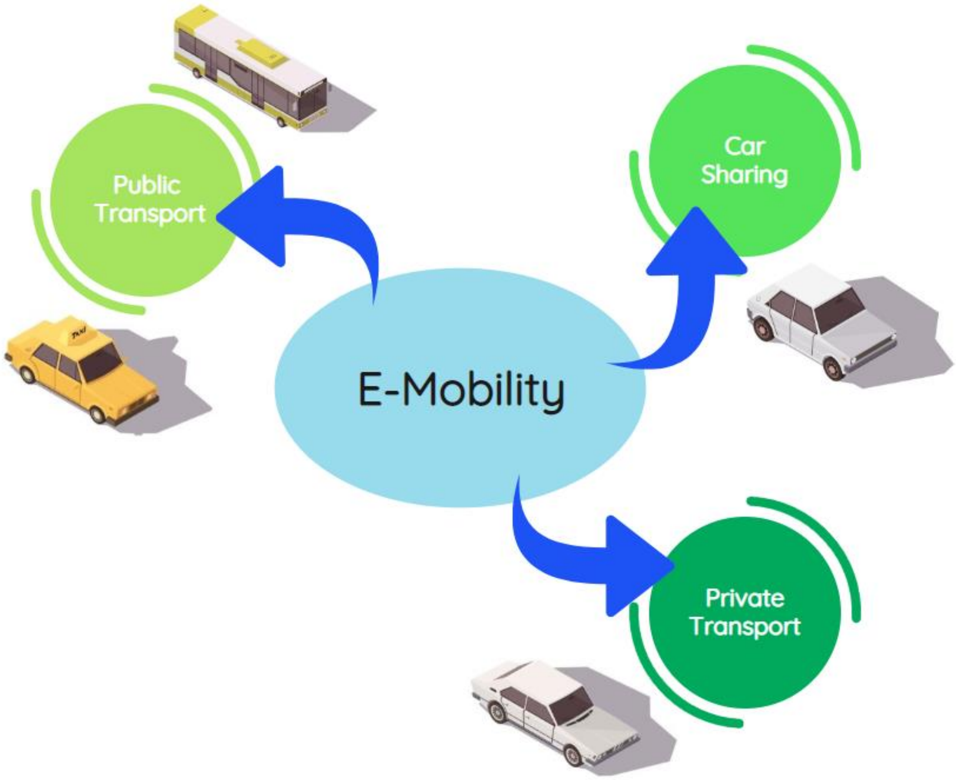


Figure 6.1 Main means of transport involved in E-Mobility

In fact, the BSSs can be used in a shared way and placed at the bus stands, in strategic points of prearranged routes or in the areas of vehicle storage as regards buses whose routine is relatively predictable and at taxi stands or parking areas such as parking near stations, airports, hotels or shopping centers for taxis on duty that unlike scheduled public transport do not follow fixed routes. The installation of BSSs in these locations would solve the problem of limited range for some type of electric vehicles.
One thing is for sure: changes related to autonomous, shared and electric mobility will considerably rewrite the structure of road transport in the coming decades.

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